Sensing and Feedback of Everyday Activities to Promote Environmental Behaviors

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This is to certify that I have examined this copy of a doctoral dissertation by

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and have found that it is complete and satisfactory in all respects,
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Abstract

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With population increases, global economic growth, and shifts in climate, the world is facing an unprecedented demand for resources that are becomingly increasingly scarce. Although often overlooked, our everyday activities such as commuting to work, showering, and clothes washing can have significant impact on the environment. The central problem addressed in this dissertation is not that humans negatively impact the environment—indeed, some amount of impact is unavoidable—but rather that we have insufficient means to monitor and understand this impact and to help change our behavior if we so desire. This dissertation focuses on creating *new types of sensors to monitor and infer everyday human activity* such as driving to work or taking a shower and taking this sensed information and *feeding it back* to the user in novel, engaging, and informative ways *with the goal of increasing awareness and promoting environmentally responsible behavior*. We refer to these sensing and feedback systems as *eco-feedback technology*. Our research takes advantage of a number of technology trends including the increasingly low cost of fast computation, advances in machine learning, and the prevalence and affordability of new types of display mediums (*e.g.,* mobile phones) to design systems never before possible.

This dissertation provides a theoretical perspective with which to guide the design of new eco-feedback systems as well as specific formative and technical contributions for eco-feedback in the domains of personal transportation and water usage. Key contributions include the invention of new

low-cost sensing systems for monitoring and inferring transit routines and disaggregated water usage in the home along with eco-feedback visualizations that take advantage of this unprecedented data. The approaches, empirical findings and a design space for eco-feedback should be of interest to researchers working on eco-feedback in HCI, Ubicomp and environmental psychology, as well as to practitioners and designers tasked with constructing new types of eco-feedback systems and/or utility bills. More broadly, this dissertation also has implications for the construction of sensing and feedback technology in general, including domains such as persuasive technology, personal informatics, and health behavior change.

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This has been a challenging marathon intermixed with high endurance sprints for good measure. Thankfully, however, this was not a marathon that I ran alone. Dissertations carry only one name but this text represents the efforts of many—from my collaborators to my family and friends, I could not have done this without you.

I want to begin by thanking my graduate advisors: James Landay and Shwetak Patel. Your complementary perspectives, experiences, and expertise made me a better researcher. James, thank you for taking a risk on me, imparting your career wisdom, and always pushing me to reach my full potential. Shwetak, thank you for adopting me into the UbiComp Lab; your creativity, energy, and vision serve as an inspiration to many (including me).

A common trait I have found across many successful graduate students is a strong, supportive family. My case is no exception. Thanks to my parents, sister, and extended family. You provided encouragement when needed. My parents were with me when I decided to attend graduate school, and they have been there for me every single day since (roughly 3,786 days in all including two Master's degrees and, now, a PhD). Their support has been unwavering and allowed me to push through even the most difficult times. I owe them much more than a dedication, but it will have to do for now.

During graduate school, I have had the fortunate pleasure to be surrounded by some of the best HCI/Ubicomp graduate students in the world (in my humble opinion at least). In Landay's group, I must recognize Scott Saponas for his cleverness, unmatched engineering skill, and showing me the infamous "off the rails" 360 dunk during our HCI lab slam dunk contests; Kate Everitt for our thoughtful research discussions and cathartic vents (including PL monster); Susumu Harada for his mindfulness and dedication to accessibility research; Michael Toomim for his amazing creativity, intelligence, and friendship; Kayur Patel for his sociability and kindness (and for letting me camp out on his couch for two weeks after returning from Barcelona), and Richard Davis for his smile and booming voice.

In Shwetak's UbiComp lab, I am astonished almost daily with the mixture of intellect, creativity, and kindness of this group. It was a pleasure working with all of you. I want to specifically recognize Gabe Cohn and Sidhant Gupta for giving me a chance to mentor them, however informally, in their first year at UW; by their second year, it would seem, it was more common for me to be learning from them than the other way around. The (now) most senior member of the lab, Eric Larson, deserves recognition as well. Of all my working relationships and collaborations in graduate school, one of the richest and most satisfying has been with Eric Larson. Without question, Eric was instrumental in helping make HydroSense what it is today. His background in signal processing, electrical engineering, and machine learning allowed us to pursue a much grander research vision than would have otherwise been possible. In addition, his patience, intelligence, diligence and warmth are traits that all researchers desire but few embody. I am grateful for the time we worked together and for our friendship.

UbiGreen had many moving parts and was my first Sustainable HCI project. Thanks to all of my collaborators for their patience and support as I made mistakes and (eventually) recovered. In particular, I would like to thank Jen Mankoff for her support and leadership on this project, Pedja Klasnja for leading the two transit-related formative studies, Tawanna Dillahunt for running participants in Pittsburgh (and essentially serving as my other half for a few months), and to my former Intel Research colleagues: Sunny Consolvo and Beverly Harrison for their insights and help. Finally, thanks to high school student (at the time), Beth Corry, for her visual design work.

HydroSense was the largest research effort I have experienced to date; thus, there are a lot of people to acknowledge. In addition to Eric and myself, the person who spent the most time and effort on Hydro was Tim B. Campbell—perhaps the greatest undergrad in the history of UbiComp Labs if not the most energetic and creative. Thanks also to Gabe Cohn and Tien-Jui Lee for their help on designing and building the ground truth sensors, to Michael Chou, Conor Haggerty, and Alex Horton for their help with data collection, to Les Atlas for his signal processing advice, to Elliot Saba for his work on Gaussian mixture models in the Hydro2 algorithms, and to Eric Swanson for his (more recent) flow inference work.

I started the water display work with Marilyn Ostergren in 2009 (just after HydroSense got rolling). Thanks for sticking by me Marilyn and for your hard work at the beginning and at the end. Thanks also to the wonderful set of undergraduates that volunteered and worked on this project, many of whom came from Students Expressing Environmental Dedication, the on-campus environmental student organization at UW. Thanks to Josh Peterson, Fabia Fu, Mazhengmin “Cissy” Bai, Solai Ramanathan, and Inness Wragg. We accomplished much in a short period of time. I could not have done it without you. Thanks also to Inness, Sara Sheridan, and Marilyn for their visual design work on this project and to Inness as well for some help with figures in this dissertation.

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Finally, there are a number of people who deserve thanks and acknowledgement but don't fit cleanly into the groups above. This includes water industry experts and representatives: Al Dietemann, Ray Hoffman, and Bob Alpers at Seattle Public Utilities and Amy Vickers (author of the Handbook of Water Use and Conservation) for their help and support. Thanks also to Jerrod Larson for recommending SurveyGizmo; to Johnny Rodgers for our thoughtful discussions about eco-feedback and the eco-feedback design space (I'm sorry we never got a chance to work together more formally); to Paul Dourish who serves as inspiration even after all of these years; to Stacey Kuznetsov for supplying me with unpublished UpStream imagery and allowing me to use them in this dissertation; to Carrie Armel and Eric Hekler for providing me with a deeper understanding of human behavior through their respective disciplines and for taking the time to review my work along the way; to Neal Lathia for the hiking (and lack thereof); to Danny Muscoplat and David Harris for sticking by me since middle school (from Comedy Sportz to CS professor, who knew?); to Lindsay Michimoto for being the best graduate academic advisor one could ask for (and who has probably supported more PhDs than the NSF, emotionally at least).

And last but not least: thanks to my wife, Leah, who I only met halfway through graduate school and yet has managed to have the biggest impact on the way I think about life, research, and the value of a good crossword puzzle. Her ability to deconstruct problems and her propensity for adventure have inspired and pushed me to be a better person and researcher. We share a kinship for tackling hard problems; a key attribute, perhaps, in a successful life together.

DEDICATION

To my parents: for their unwavering love and support.

I could not have done this without you.

Chapter 1
Introduction

The United States consumes one quarter of the world's energy resources, despite accounting for less than five percent of the world's population (US Department of Energy, 2002). While industrial and commercial consumption account for a large portion of this use, individual behavior also plays a significant role. Home energy use and personal travel comprise 28% of US energy consumption and 41% of US CO2 emissions (Shui and Dowlatabadi, 2005). The residential sector alone accounts for 21% of US energy consumption. Individual behavior also plays a significant role in water usage: residential water use accounts for 50-80% of public water supply systems and 22% of total use in the US[1] (Vickers, 2001; Kenny *et al.*, 2009). According to US government estimates, 36 states will face serious water shortages within the next decade (Nesius, 2007).

So, although often overlooked, our everyday consumption behaviors such as commuting to work, showering, and clothes washing can have a significant impact on the environment. The central problem addressed in this dissertation is not that humans negatively impact the environment—indeed, some amount of impact is unavoidable—but rather that we have insufficient means to monitor and understand this impact—and to change if we so desire. My dissertation research focuses specifically on creating *new types of sensors to monitor and infer everyday human activity* such as driving to work or taking a shower and then taking this sensed information and *feeding it back* to the user in novel, engaging, and informative ways *with the goal of increasing awareness and promoting environmentally responsible behavior*.

[1] This figure excludes water use from the thermoelectric industry because most of this use is *non-consumptive* (see USGS, 2005). Thermoelectric power plants, which are typically coal, gas, or nuclear fuel based, rely on water to condense steam. This process withdraws large volumes of water but returns nearly all of it back to the source with little consumptive use (albeit with some environmental consequences, *e.g.*, thermal pollution). We return to this distinction in the Water section of the Related Work chapter (Chapter 2).

To date, the primary methods applied to reducing consumption have largely been technological and economic (Armel, 2008). For example, the production of hybrid vehicles has been emphasized as a major solution to CO_2 reduction and oil dependence. However, there is growing evidence that a human-centered, *behavioral* approach should also be pursued to educate, inform, and motivate environmentally sustainable human behaviors. Indeed, it has been consistently found that energy use can differ by *two* to *three* times in identical homes, occupied by people with similar demographics (Socolow, 1978; Winett *et al.*, 1979). For example, in a study evaluating the energy consumption of 10 identical Habitat for Humanity all-electric homes outfitted with the same appliances and equipment, homes exhibited a large range in energy consumption, with the most energy intensive home consuming *2.6 times* more energy than the least (Socolow, 1978). Similarly, with a change in occupancy, the energy usage by the new occupants could not be predicted based on the usage of the former occupants (Sonderegger, 1978). Such findings reveal how differences in human behavior can significantly affect resource consumption and suggest that intervention strategies to promote sustainable behaviors could result in significant reductions of energy and water usage (and perhaps in other environmentally relevant areas as well).

A key problem is that most people are unaware of how their daily activities affect the environment and have few resources to find out. For example, a majority of people have no means of judging their resource consumption other than monthly (or bi-monthly) electricity, water and gas bills which, even then, only provide aggregate details on consumption and nothing related to environmental impact. Kempton and Layne (1994) draw the analogy that this would be like shopping at a grocery store where the goods are not marked with individual prices and the only feedback received about purchasing is through a monthly bill that provides one aggregate, total cost (*e.g.,* "You spent $642 for 1527 food units in April")—see Figure 1.1a. Yet, this is precisely the level of feedback that we receive about consumption activities in the home, which makes it difficult to economize and judge the relative merits of individual conservation practices (Dennis, 1990). New emerging sensing and feedback systems, such as the ones reported in this dissertation, promise to transform how residents think about and understand consumption in the home.

For transportation, the availability of feedback is even more sparse and varied. Although odometers, fuel gauges, and even number of trips to the gas station provide us with some indication of our driving behavior and routines, there are no forms of feedback that integrate all of our transit—

Figure 1.1: (a) Imagine if prices were not marked on goods at the grocery store and instead of paying and receiving an itemized bill at checkout, you had to wait until the end of the month where you simply received a bill with total aggregate cost. This is the analogy drawn by Kempton and Layne (1994) to depict the amount of information available currently for many of the other resources we consume in our lives. (b) Water, gas, and electrical meters are not meant to be read and understood by the consumer but rather by trained utility personnel for bill tracking purposes. Most people receive feedback through their monthly or bi-monthly bill, which only provides one number temporally disconnected from the consumption itself making it difficult to assess what activities comprise the most significant usage.

walking, bicycling, bus riding and more—into a single display. Perhaps partly as a consequence, few of us think about or understand opportunities for greener transit when they exist—even if they are available along our typical driving paths. An integrated display that senses and feeds back all manifestations of human movement could reveal cost savings for different modes of transit, suggest eco-friendly alternatives when they exist, and, at the very least, provide a breakdown of the different amounts in which we walk, bike, drive or engage in other forms of transit to better understand our personal impact on the environment. Even if one were interested in this information currently, it would be very difficult to derive and take careful diligence and effort. There is an opportunity here for sensing and feedback systems.

Although historically a variety of methods have been used to promote proenvironmental behaviors ranging from informational media campaigns to monetary incentives (see Katzev and Johnson, 1987), feedback has been shown to be one of the most effective strategies in overcoming the disconnect between activity and environmental impact (Geller, 1982). For example, over 30 years of investigations into the effect of feedback on electricity consumption reveals typical reductions between 5 and 20% depending on the frequency, duration, specificity, and type of feedback (see Chapters 3 and 4). These are significant reductions. For example, a 15% reduction in electricity across US households represents nearly 200 billion kWh of electricity per year—equivalent to the power output of 16 nuclear power plants for a year. Similarly, a 15% reduction in water usage across

US households would save an estimated 2.7 billion gallons *per day* and more than $2 billion per year (American Water Works Association, 2001).

While a majority of research into the effects of feedback on environmentally relevant behavior has focused on energy consumption, our goal was to investigate if and how eco-feedback could be applied to other areas such as transportation and water usage. In addition, we were particularly interested in exploring the link between *sensing* systems and *feedback* visualizations. How can we sense human activity at a more granular level than has traditionally been possible and then use this data to create novel forms of engaging and actionable feedback? What form should this feedback take—how should it be designed? The goal here is not to replicate existing sensing or metering technologies and, say, simply focus on making this information more accessible but rather to explore new levels of feedback never before possible, enabled by fundamentally new types of sensing systems.

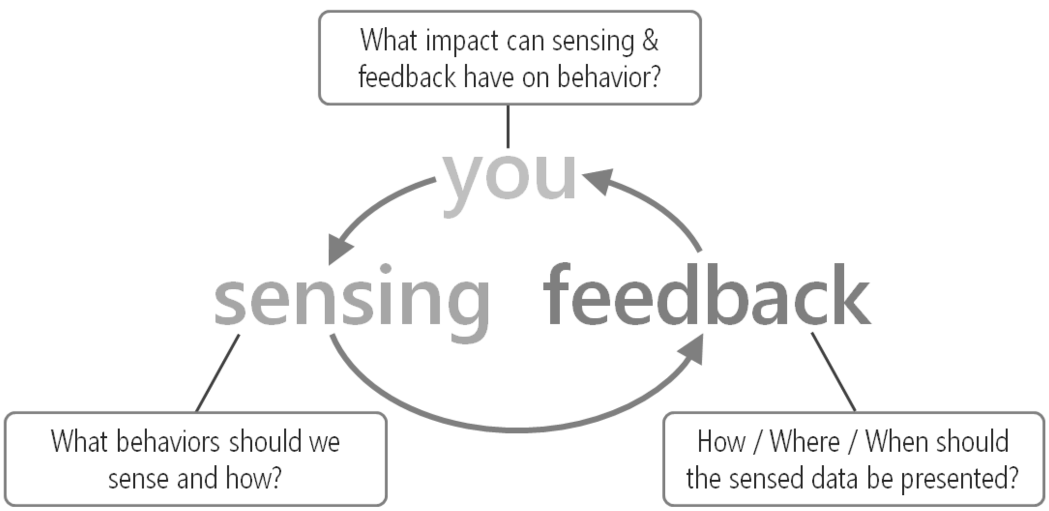

Figure 1.2: The sensing and feedback loop for human behavior including core underlying research questions. A sensing system *senses human behavior*, which is input into the *feedback system* and *visualized* in order to engage, inform and *potentially change behavior*. Changes in behavior (or the lack thereof) are then sensed by the underlying sensing system and the loop continues.

1.1 SENSING AND FEEDBACK

Human behavior is complex—so much so that it is a fundamental topic of inquiry in such diverse fields of research as philosophy, economics, sociology, psychology and, my own discipline, human-computer interaction (to name a few). As computing shifts off the desktop and integrates itself into the various forms of human life (Weiser, 1991), there is an increasing role for computing to not be just a productivity tool but to actually fundamentally improve lives—by making us more fit, more informed, and more aware of ourselves and the world around us. Sensing and feedback systems for physical activity to improve personal health, for example, have received a tremendous amount of attention in the last decade (*e.g.,* Assogba and Donath 2009; Bravata *et al.* 2007; Consolvo, 2004; Consolvo, 2008; Intille 2004; Maitland *et al.* 2006; Tudor-Locke *et al.* 2004).

1.1.1 Potential of Sensing and Feedback

Sensing and feedback has the potential to be an external, objective eye on our behavior—a way of acquiring insights into ourselves that were previously not possible (Figure 1.2). When highlighting the potential of sensing and feedback systems, I often use the analogy of a mirror. Imagine living during the invention of the mirror—for the first time in history, outside of our shadows or reflections in water, we could see ourselves as others do[2]. Think of how this must have changed self-perception and self-identity. But even the mirror plays tricks on us—though most of us rely on this old form of technology daily, its effect becomes limited with time. We look in the mirror and often focus on what *we want to see*. We present ourselves in the best light *to* ourselves—we prepare before looking in the mirror by sucking in our gut or forming a certain desirable expression on our faces. In this way, we don't always see a realistic portrayal of ourselves.

Thus, the mirror analogy stops short of highlighting the full potential of sensing and feedback systems—not just because it focuses on the external image of who we are but also because we prepare ourselves for it. A mirror rarely catches us off guard. One can turn towards a more modern technology, the camera, for a potentially more adept analogy. Like the mirror, the camera provides an external view of ourselves. And although we might pose and prepare for a picture, the spontaneous and perhaps furtive shots are the ones that can shock us—that can reveal the gut that we may have unconsciously hid from ourselves or that a style of clothes or haircut were not so befitting after all. This is only but a small window into the potential of sensing and feedback systems of the future.

Of course, unlike a mirror or a camera, these systems are not focused on *what we look like* but rather on *how we behave.* In this way, sensing and feedback is a *mirror for behavior*; a way of reflecting on and understanding ourselves from a different perspective. In the future, these systems will not only provide objective measures and timelines of behavior but the more sophisticated ones

[2] Human kind has long been interested in viewing its own image. The earliest crafted mirrors were pieces of polished stone or obsidian followed later by copper and bronze. Archeologists have found mirrors dating back to 6,000 BC though they did not come into widespread production until the 16th century (where they remained a costly luxury until the 19th century). Throughout history, mirrors have inspired tales of myths and magic, stimulated psychological inquiry and analysis, and even provoked new tests of intelligence—the ability to recognize one's own reflection in the mirror is seen as a sign of intelligence. For more background on mirrors, see Melchior-Bonnet and Jewett, 2001.

will actively learn and adapt models to most effectively motivate and coach us to become healthier/fitter/better.

1.1.2 Types of Feedback

So, how does feedback work and why? As far back as 1927, feedback has been shown to be an important means of modifying behavior (Thorndike, 1927). Feedback provides a basic mechanism with which to monitor and compare behavior and allows an individual to better evaluate their performance. Becker (1978) provides an example of how, during target practice, knowledge about where each round hits a target helps the shooter improve his or her aim. This *low-level feedback* can provide explicit detail about how to change or improve specific behavior. In addition, feedback about how many targets have been hit after 10 rounds allows the shooter to determine whether his or her personal goals have been met. Such *high-level feedback* can help improve performance by motivating a person to try harder or persist longer at a task (Kluger and DeNisi, 1996; Locke and Latham, 2002). Feedback appears to work because it has both informational and motivational properties: it can provide a basis for assessment and action and enable progress towards a goal (Aitken *et al.*, 1994). As a result, feedback can be an effective means to alter human behavior.

It's not just the presence of feedback that can change behavior but *how* that feedback is provided (*e.g.,* Figure 1.3). Let's consider driving for example—imagine that we want to know our vehicle's gas mileage and whether or not it is reasonably close to the Environmental Protection Agency's (EPA) fuel economy estimate. Our sources of feedback are an odometer and a fuel gauge, which provide us with information on miles traveled and fuel amount; however, these two sources of information must be carefully tracked by hand and combined to calculate gas mileage. Thus, although the fuel mileage information is latent within the two information sources provided, it is not visualized in an easy-to-use manner. Newer cars, however, provide this information in real-time right in the dashboard making it much easier to see if our gas mileage is better or worse than government estimates.

The Toyota Prius hybrid goes even further—its dashboard shows not just the average fuel mileage but the *current* in-the-moment fuel mileage as well as fuel mileage in the last 30 minutes (in five minute intervals through a scrolling bar graph). This simple addition in information has allowed drivers to drive more efficiently, some reaching average fuel economies far beyond the EPA-estimates (*e.g.,* Woodyard, 2008; see also Chapter 2). With the emergence of cheap radar, other forms of feedback on driving have emerged in the last decade or so, which are not even located in the car. These "vehicle activated signs" provide redundant information with what is already available in the vehicle: namely, your current speed; however, studies have shown that they reduce driver speed by an average of 10-15% (Goetz, 2011)[3]. Some cities have taken these signs and added a persuasive component to further encourage speed reductions (*e.g.,* Figure 1.3d). I introduce these examples to make a key point that we explore in this dissertation: there is a difference between information and the way that information is presented—and these differences can greatly impact the information's effect on our behaviors.

Figure 1.3: Different ways of presenting feedback about driving behavior: (a) the traditional dashboard, (b) the Toyota Prius dashboard, (c) a vehicle activated sign that displays sensed speeds of oncoming traffic, and (d) a clever variation on (c) that changes the currently sensed speed into a persuasive message. Each presentation can have a different impact on behavior.

1.1.3 Eco-Feedback: Sensing and Feedback for Environmentally Impactful Behaviors

This dissertation focuses on developing new types of sensing and feedback systems for everyday human behaviors that impact the environment around us. These sensing and feedback systems, which we call *eco-feedback technology*, sense and provide feedback on individual or group behaviors with a goal of increasing awareness and/or reducing the negative environmental impact (adapted from Holmes 2007; McCalley and Midden, 1998). Eco-feedback technology is based on the working hypothesis that most people lack awareness and understanding about how their everyday behaviors such as driving to work or showering affect the environment; technology may bridge this "environmental literacy gap" by automatically sensing these activities and feeding related

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[3] Admittedly, there are actually a number of differences between the dashboard speedometer and the vehicle activated sign—differences, which could very well account for the reduced driver speeds in these areas. But this does not undermine my point, only enhances it. First, the signs themselves always show the speed limit along with the currently sensed speed—this allows the driver to easily compare his/her own speed to the limit and adapt as necessary. As we discuss in Chapter 4, comparison can be very effective as a complement to straight feedback. Second, the signs themselves often provoke a feeling of surveillance or "wrong-doing" as they are placed by local law enforcement or government agencies. This may induce a feeling of fear further encouraging a reduction in speed. Finally, unlike your in-car dashboard, the sensed speed displayed on the sign is *publically visible*. Consequently, there are *normative* or *social* pressures to conform to the legal speed.

information back through computerized means (*e.g.,* mobile phones, ambient displays, or online visualizations).

With the advent of low-cost sensing technologies, fast computation, and advances in machine learning, we now have the potential to provide new types of feedback, which are personalized, interactive, increasingly motivating, and, perhaps most importantly, tied to specific activities (*e.g.,* driving to work, taking a shower, watching TV). Moreover, the next generation of resource measurement systems (often referred to as "smart meters") will soon provide real-time (or near real-time) data on electricity, gas, and water usage in homes and businesses. This will produce tremendous amounts of data that can be analyzed and fed back to the user, creating even more opportunities for eco-feedback technology research.

In addition, advances and increased accessibility to new display mediums offers a wide range of ways to feedback consumption information (*e.g.,* mobile phones, internet, home automation centers). Such advances in both *sensing* and *feedback* provide a rich space of opportunities for new types of eco-feedback that could not be considered in the past. Human-Computer Interaction (HCI) and Ubiquitous Computing (Ubicomp) researchers are well positioned to apply their expertise in sensing and interface design to create a new generation of eco-feedback technology.

Indeed, thus far, HCI and Ubicomp researchers have built eco-feedback technologies for a variety of domains including energy consumption (Gustafsson and Gyllenswärd, 2005; Petersen, 2009; Yun, 2009), water usage (Arroyo *et al.*, 2005; Kuznetsov and Paulos, 2010), air quality (Kim, 2009; Kim, 2010; Kuznetsov, 2011) consumer retail purchases (Tomlinson, 2008), and waste disposal practices (Holstius, 2004; Paulos and Jenkins, 2006); see Figure 1.4. In this dissertation, we focus specifically on the link between *sensing* and *feedback*—the ways in which they interact and how this enables

Figure 1.4: Examples of eco-feedback technology from the HCI and Ubicomp research communities for (a) retail purchases (Tomlinson, 2008), (b) energy usage (Petersen, 2009), (c) waste disposal (Holstius, 2004), and (d) water usage (Kuznetsov, 2011).

new types of eco-feedback particularly for personal transportation and residential water usage. In addition, as eco-feedback is still an emerging area of research, particularly in HCI and Ubicomp, we explore design guidelines to ease the construction of these systems and provide a theoretical basis.

1.2 RESEARCH APPROACH

We have followed an iterative design approach, beginning with formative studies of both personal transportation and household water usage that then informed the design and development of our sensing and feedback technology. For sensing, our evaluations began in the lab with controlled experiments followed by controlled experiments in the field and finally real world deployments. For the feedback interfaces, our evaluations range from large scale online survey studies to smaller scale ethnographically inspired interviews to actual field deployments. Of the high level research questions presented in the eco-feedback diagram in Figure 1.2, this dissertation focuses primarily on designing and evaluating sensing and feedback with a smaller emphasis on how this changes behavior. As noted in Chapter 3, our goal here—and that we argue of any HCI/Ubicomp researcher involved in eco-feedback research—is to provide a strong foundation with which companies and/or environmental psychologists can take our ideas/findings and evaluate them in larger-scale, randomized control trials. This can, of course, be accomplished through collaboration as well; however, such experiments were beyond the scope of this research.

The results in this dissertation should benefit researchers working in the area of eco-feedback including researchers from HCI/Ubicomp, environmental and social psychology, as well as water resource management scientists and field workers. Our findings from Chapters 6 and 9 have implications not just for the design of computerized eco-feedback but also for older, more traditional forms of eco-feedback such as bills and online websites.

1.3 THESIS GOALS AND CONTRIBUTIONS

At a high level, the goal of this dissertation has been to design, develop, and evaluate sensing and feedback technologies to promote proenvironmental behavior[4] and decision making. Our approach was fourfold: (1) to draw upon behavioral science, environmental psychology, information visualization and past Sustainable HCI research to create a series of guidelines and dimensions to

[4] It is not always clear what, exactly, constitutes "proenvironmental behavior." Stern (2000b) and Steg and Vlek (2009) define *environmental behavior* as any behavior that changes the availability of materials or energy from the environment or alter the structure and dynamics of ecosystems or the biosphere and *proenvironmental behavior* as behavior that harms the environment as little as possible. In this thesis, we use environmental behavior and proenvironmental behavior interchangeably to fit the latter definition: essentially, behavior that reduces harm to the environment.

help both the *design* and *evaluation* of eco-feedback systems; (2) to study environmentally impactful human behaviors around transit and water usage to uncover insights into how eco-feedback may play a role; (3) to create and evaluate new types of sensing systems to enable eco-feedback systems that were previously not possible; (4) and to design, develop and evaluate novel eco-feedback interfaces and systems themselves. Below, we trace out the underlying research questions within each of these areas and the approach we took to address these questions. Note that although we examine and study both transportation and water usage, the primary emphasis in this dissertation is on water (which is the main focus in four of the eight content chapters).

1.3.1 Defining the Role of HCI in Eco-Feedback Research

The first goal of this dissertation is to examine the role of HCI in the design and evaluation of eco-feedback technology. While the emphasis of eco-feedback technology is to provide feedback on individual or group behaviors to *reduce environmental impact*, few HCI eco-feedback studies have even attempted to measure behavior change. And although eco-feedback is often seen as an extension of persuasive technology[5] (Fogg, 2002), particularly amongst the HCI/Ubicomp research community, eco-feedback actually extends back more than 40 years in fields such as environmental psychology and applied social psychology. This gives rise to two interrelated questions: (1) What can HCI learn from environmental psychology and related disciplines; and (2) what should be the role of the HCI community in contributing to eco-feedback research?

In Chapter 3, we reflect on the current state of eco-feedback technology through a comparative survey of 44 papers studying eco-feedback technology in the HCI/Ubicomp literature and 12 papers within the environmental psychology literature. We show that although HCI/Ubicomp researchers tend not to evaluate eco-feedback systems in longitudinal behavioral intervention trials common in environmental psychology, there is a strong role for HCI/Ubicomp research. Environmental psychologists have not traditionally been concerned with the design and advancement of the intervention artifact that they are testing, rather its effect on behavior. In contrast, HCI/Ubicomp researchers in eco-feedback research have focused on new sensing methods, novel information visualization strategies, and new types of interfaces and interactions. These are core areas of HCI/Ubicomp expertise. We argue that given the shared pursuits of the two fields, a key outcome

[5] The distinction between what qualifies as a *persuasive technology* versus an *eco-feedback technology* is not always clear. I tend to use the word "persuasive" with care because in common parlance, it often has negative connotations with feelings of "manipulation" and "coercion." I would agree that all eco-feedback has a persuasive element in that it has the *potential to persuade* but there are clearly some eco-feedback designs where the main focal point is to *inform* rather than *persuade*. We return to this discussion and the role of *information* versus *persuasion* in Chapter 4.

should be that the two disciplines work more closely together to design and evaluate eco-feedback systems and interfaces.

1.3.2 Transportation and Residential Water Usage Attitudes, Behaviors, and Routines

Before designing eco-feedback systems for a particular environmental domain, we must understand the decisions, constraints, attitudes and behaviors within the domain itself. For example, what reasons do people have for preferring car driving over bus transit? And, how much water do people think an average shower uses? The second goal of this thesis, then, was to quantitatively and qualitatively assess attitudes, perceptions, behaviors and routines around transportation and water usage. Although past work has explored some of these issues (*e.g.,* Chetty *et al.,* 2008; Woodruff *et al.,* 2008; Strengers *et al.,* 2008), our focus here was particularly on uncovering opportunities for eco-feedback. In addition, many of the past formative investigations in HCI have been conducted around energy usage (*e.g.,* Chetty *et al.*, 2007), with much less attention towards transportation and water.

1.3.2.1 Transit

For transit, we performed two formative studies to examine motives, attitudes and behaviors around driving and alternative transit (Chapter 5). These studies included: (1) an online survey of 63 respondents to explore how people make transportation decisions, their willingness to engage in green travel, and their reactions to our application design concepts; (2) a one-week experience sampling (ESM) study with seven participants that explored in-the-moment reasoning about transportation choices.

Our results show that a number of factors underlie a person’s choice for transit including travel time, flexibility and cost. Interestingly, only a small subset of our respondents (19%) considered the environmental impact of transit as one of their top three priorities when making transit decisions; however, far more were interested in trying to travel in more eco-friendly ways. Additional motivations cited included opportunities for exercise, relaxation, and the ability to accomplish other tasks. These findings can be incorporated in transit-based eco-feedback, as we do in Chapter 5.

1.3.2.2 Water

To inform the design of water usage feedback, we conducted an online survey of 656 respondents (Chapter 6). The survey explored questions such as: How well do people understand water usage amounts of common everyday activities like showering and toilet usage? What factors influence water consumption? How do people think about water as a resource? What are their primary motivators for conservation?

We found ample evidence to support the need for different sorts of water feedback than is currently available in most homes. A rather large number of our respondents (33%) received no monitoring or feedback about their consumption whatsoever. Our findings also suggest that most people have an inaccurate conception of what fixtures and appliances typically the most water. For example, approximately a quarter of respondents ranked dishwasher and bath among the top three water consumers in the home (dishwashers tend to be the least water consuming fixture/appliance in the home). We also found that our respondents tended to grossly *underestimate* the amount of water use various common activities consumed such as showering and lawn watering. Combined, these findings point to the potential of water eco-feedback systems for increasing consumption knowledge and water literacy.

1.3.3 Building and Evaluating Sensing Systems for Transportation and Water Usage

The third goal of this dissertation was to create highly granular sensing technologies for transit and water usage behaviors to enable new types of eco-feedback applications. These systems target sensing opportunities identified in the aforementioned formative studies. For example, how could we build a sensing system that is capable of informing residents about how much water they use at each fixture and appliance in their home?

1.3.3.1 Transit

To build eco-feedback systems for personal transportation, we wanted to be able to sense a range of transit modes from bicycling and walking to taking the bus and driving a car. Although previous research has examined using wearable sensors (Choudhury *et al.*, 2008), cell tower infrastructure (Sohn *et al.*, 2006), or self-report (Froehlich *et al.*, 2006) to track human transit patterns, our research is the first to combine these three methods into a single working system. This enabled a new type of transit feedback system: UbiGreen (covered in a subsequent subsection below on novel eco-feedback interfaces).

1.3.3.2 Water

Our formative water survey showed a profound lack of knowledge and understanding about the consumption of common water usage activities in the home. Current state-of-the-art water monitoring systems only provide water usage data at aggregate levels (*e.g.,* smart meters). These water sensors allow the water supplier to sample consumption information down to 15-minute intervals but the focus is still on bill tracking and not on feeding this information back to the consumer. In addition, these solutions only focus on aggregate usage amounts—one number for the whole home—making it difficult to ascertain exactly *where* and *for what activity* water use is occurring. Finally, as these monitoring solutions are utility driven, they require professional installation and the data is not "owned" by the household but instead by the utility.

To address these shortcoming, we developed HydroSense, a real-time water usage sensing system that could be installed by the homeowner him or herself and provides *disaggregate*[6] water consumption information down to individual fixtures (*e.g.,* the upstairs bathroom toilet or the downstairs bathroom faucet). HydroSense represents a significant advance over prior research in several regards: (1) HydroSense can be *easily installed* at any accessible location within a home's existing water infrastructure without the need for a plumber (which greatly impacts the overall cost of the device); (2) HydroSense uses *pressure changes* to both *identify the individual fixture* (or fixtures) in which water is being used as well as to provide *flow estimates*; (3) and, given sufficient calibration, HydroSense can discriminate between hot and cold water usage.

To validate HydroSense, we performed two evaluations: (1) a controlled experimental evaluation in 10 homes of staged water usage events and (2) a longitudinal five-week evaluation in five homes of real-world water usage. In the controlled experiment, our algorithms successfully identified *individual fixtures* with 97.9% aggregate accuracy. We also show that an appropriately located and calibrated system can estimate water usage with error rates comparable to empirical studies of traditional utility-supplied water meters. In the second evaluation, we extended and adapted our initial inference algorithm to shift from being a strict template-matching approach to one that is based on a Bayesian model. Inspired by algorithms in speech recognition, our novel Bayesian approach incorporates template matching, a language model, grammar, and prior probabilities. Here, we show that with a single pressure sensor, our probabilistic algorithm can classify pre-segmented real-world water usage at the fixture level with 90% accuracy and at the fixture-category level with 96% accuracy. With two pressure sensors, these accuracies increase to 94% and 98%

[6] *Aggregate* and *disaggregate* are the two commonly used terms in the resource sensing and utility communities to distinguish between *overall consumption measurements* (aggregate) and *per-fixture/per-appliance measurements* (disaggregate). In the case of water, HydroSense tracks consumption at the disaggregate level—meaning that it senses water use at individual fixtures and appliances (and it does so from a single sensing point). Although beyond the scope of this dissertation, energy disaggregation sensing is a very hot topic of research at the moment. Please see our paper *Disaggregated End-Use Energy Sensing for the Smart Grid* for more information (Froehlich *et al.*, 2011).

respectively. Our evaluations demonstrate the effectiveness of our algorithms but also highlight the importance of conducting real-world field trials of sensing technology.

1.3.4 Design, Develop, and Evaluate Novel Eco-Feedback Interfaces

Based on the sensing systems described above, our fourth and final goal was to create new types of eco-feedback systems and interfaces around this data to inform and motivate proenvironmental behaviors. Our high level objective was to rethink the ways in which we could feed back behavioral data to the user based on these new types of sensing systems. To accomplish this goal, we propose a design space for eco-feedback technology, as well as design and evaluate eco-feedback displays for transportation and for water.

1.3.4.1 An Eco-feedback Design Space

We provide an eco-feedback design space to allow designers and practitioners to approach the eco-feedback design process with a tangible structure that exposes assumptions underlying various eco-feedback techniques and provides a means to reliably compare the strengths and weaknesses of different approaches. By reviewing current feedback designs, we isolate and identify eight eco-feedback dimensions with which to build and analyze eco-feedback systems. These design dimensions (and sub-dimensions) include, for example, the spatial proximity between feedback and behavior, how the data is grouped or clustered in the display, and the comparison mechanisms used. The design space is useful both as a lens to analyze and understand the effectiveness (and ineffectiveness) of existing eco-feedback technology as well as a foundation to help build and evaluate new systems.

1.3.4.2 Transit

Because transportation is inherently a mobile activity, mobile devices are well suited to sense and provide feedback about these activities. We designed, developed, and evaluated a mobile phone application, called UbiGreen, that semi-automatically senses and feeds back information about transportation behaviors by changing the wallpaper (background display) on the user’s mobile device. We created two feedback designs in particular: a *tree design* that grows leaves, flowers, and fruit and an *arctic eco-system* that uses an ice floe and animals to represent green transit use. The goal here was not to explore the impact that UbiGreen had on transit behaviors particularly—a three week field study with no baseline data is insufficient for this—but rather to explore how glanceable, abstract, and ambient visualizations could be used and the reactions it provoked. We evaluated UbiGreen through a three-week, 12 person field study across two American cities: Seattle, WA and Pittsburgh, PA. Our findings include recommendations about the use of iconic vs. numeric representations of information, the usefulness of wallpaper as a glanceable medium, the use of narrative to build anticipation and curiosity, and suggestions for future transit-based eco-feedback systems. As this was our first eco-feedback interface evaluation, we also used these findings to inform and iterate upon our eco-feedback design space. It also influenced our water feedback designs.

1.3.4.3 Water

Although much past work has explored visualizing home resource consumption, far fewer, if any, have explored interfaces to visualize disaggregated consumption data. The goal here was to explore possible eco-feedback interfaces for the disaggregated water usage data provided by HydroSense. Questions included: given a rich set of data, what is the most effective way to present it back to the user and with what time and data granularity? In addition, given that these eco-feedback systems are meant for the home, how can these visualizations incorporate and respond to household dynamics and social context such as privacy or competition among family members?

Our approach was to create and evaluate a series of eco-feedback displays for household water consumption that were explicitly designed to explore the above questions. Some of these displays, called design probes, were intentionally created to explore points in the design space that may not even be possible with current technology, such as a display that provides per-occupant consumption data in the household. We evaluated the displays through both an online survey of 651 respondents and in-home interviews with 10 households. The findings show that simple feedback is good, privacy is a concern but it depends upon how the information is presented. Some issues were polarizing, such as the competition within the household or individual accountability, and some interfaces induced notions of guilt. Because this is one of the first studies of its kind, the findings should be valuable not only to the design of water eco-feedback displays but also in the design of other forms of disaggregated feedback.

1.4 SUMMARY OF CONTRIBUTIONS

The contributions of this dissertation can be organized around three high-level areas: *foundational* contributions, *sensing* contributions, and *feedback* contributions. Although these areas are not perfectly independent from one another—indeed, feedback systems are fundamentally dependent on the type and resolution of data from sensors in enabling or constraining the presentation of information—these divisions are useful for clearly articulating the primary contributions of this dissertation research.

1.4.1 Foundational Contributions

The foundational contributions involve motivating the need and potential for sensing and feedback systems for environmentally relevant behaviors and in identifying the role of HCI/Ubicomp within this area of research:

1. Assessing the role of HCI in the design and evaluation of eco-feedback systems.
2. Formative studies of personal transportation attitudes, behaviors and routines to inform the design of eco-feedback systems for transit.
3. Formative studies of residential water usage attitudes, behaviors and routines to inform the design of eco-feedback systems for water.

1.4.2 Sensing Contributions

The sensing contributions involve the design, development and evaluation of novel sensing methods to track environmentally impactful behaviors for personal transportation habits and water usage. The primary sensing contributions in this dissertation are for water. Sensing transit activities are a secondary contribution:

4. A method for tracking transit behaviors using automated sensing and self-report.
5. Design and evaluation of a sensor for automatically determining fixture-level water usage events from a single, low-cost sensor. This contribution is three-fold:
    a. A method for identifying and classifying water use through a pressure sensor installed in an arbitrary location on the home plumbing system.
    b. A method for calculating real-time flow estimates for disaggregated events.
    c. A method for disaggregating overlapping or compound water events.

1.4.3 Feedback Contributions

The feedback contributions involve the design and evaluation of novel eco-feedback interfaces for water usage and personal transportation as enabled by the new sensing systems outlined above.

6. An eco-feedback design space to guide the development and evaluation of eco-feedback systems.

7. The design, development and evaluation of UbiGreen, an eco-feedback application to promote green transportation habits.
8. The design and evaluation of water usage feedback displays, studying specific dimensions of feedback (*e.g.,* level of data granularity) as well as social and household context (*e.g.,* issues of privacy).

1.4.4 Summary

In summary, this dissertation contributes new knowledge around the construction and evaluation of eco-feedback systems. It provides both a theoretical and formative perspective with which to guide the design of new eco-feedback systems as well as new methods and applications, in particular, for eco-feedback in the domains of personal transportation and water usage. The key technical contributions are the invention of new low-cost sensing systems for monitoring and inferring transit routines and disaggregated water usage in the home along with eco-feedback systems that take advantage of this unprecedented data. This dissertation should be of interest to those working in Sustainable HCI and eco-feedback technology including researchers in HCI, Ubicomp and environmental psychology as well as practitioners and designers tasked with constructing new types of eco-feedback systems and/or utility bills. More broadly, this dissertation has implications for the construction of sensing and feedback technology in the domains of persuasive technology, personal informatics, and health behavior change (*e.g.,* mobile health).

1.5 DISSERTATION ORGANIZATION

This dissertation is broken down into two parts: the first part (Chapters 2, 3 and 4) explores, reflects on, and describes the design and evaluation of eco-feedback systems in general, the role of HCI/Ubicomp in this endeavor, and strategies for going forward. The second part (Chapters 5, 6, 7, 8, and 9) describes the design and evaluation of our own eco-feedback systems, which were created, in part, based on the undertakings and findings from the preceding chapters.

Part I begins with Chapter 2 by presenting background and previous work related to sensing and feedback systems for personal transportation and water usage. Chapter 2 also contextualizes and positions eco-feedback as a research discipline within HCI/Ubicomp and draws links to the field of information visualization. Chapter 3 offers a survey of the eco-feedback research across both environmental psychology and HCI/Ubicomp, which we use to compare and contrast the design and evaluation approaches taken across the two fields and to identify areas in which HCI/Ubicomp can make the strongest contribution. Chapter 4 continues this interdisciplinary outlook and integrates findings from environmental psychology and the behavioral sciences to uncover and synthesize models of proenvironmental behavior and motivation techniques that could be utilized to more effectively design eco-feedback systems. Chapter 4 concludes by integrating these findings (and those from Chapters 2 and 3) into an eco-feedback design space, which serves both as a critical lens to evaluate existing eco-feedback systems as well as a guide to help design new ones.

Chapter 5 offers a transition point to the second part of the dissertation, which is focused specifically on personal transportation and water usage. Chapter 5 presents our first eco-feedback system: UbiGreen, a mobile phone application that semi-automatically senses and feeds back information about personal transportation routines to encourage green transit choices. Chapters 6, 7, 8, and 9 are focused on sensing and feedback systems for residential water usage. Chapter 6 provides a formative inquiry into common attitudes, beliefs, and knowledge about water usage in the home with the goal of informing the design of water sensing and feedback systems. Chapters 7 and 8 present the design and evaluation of HydroSense, a water sensing system that provides unprecedented levels of sensing granularity (down to the individual fixture) from a single installation point. Inspired by HydroSense and informed by our formative work in Chapter 6 as well as the eco-feedback design work in Chapters 3 and 4, Chapter 9 presents two sets of novel eco-feedback displays for water as well as a survey and interview-based evaluations. Finally, Chapter 10 concludes the dissertation by highlighting limitations in the preceding chapters and open areas for future work. Following this chapter, several appendices provide the study materials used in our studies including survey questions, interview scripts, and findings from our pilot studies.

Most of the work presented in this dissertation has been previously published. Chapters 3 and 4 are based on our ACM CHI2010 paper (Froehlich *et al.*, 2010) and on our HCIC2009 workshop paper (Froehlich, 2009). Chapter 5 is based on our ACM CHI2009 paper (Froehlich *et al.,* 2009a). Chapter 7 is based on both our UbiComp2009 paper (Froehlich *et al.,* 2009b) and our Personal and Mobile Computing journal paper (Larson *et al.,* 2010). Chapter 8 is based on our Pervasive2011 paper (Froehlich *et al.,* 2011). Large parts of Chapter 9 are currently in submission.

Chapter 2
Background and Related Work

Eco-feedback research spans multiple fields including environmental psychology, HCI/Ubicomp, economics and the behavioral sciences. Although only recently a target of inquiry within HCI/Ubicomp, eco-feedback research has a long history, extending back to the 1970s in other disciplines. This chapter and the next two attempt to synthesize this related literature, articulate the role of HCI/Ubicomp within eco-feedback research (Chapter 3), and integrate particularly promising findings into an eco-feedback design space (Chapter 4).

In this chapter, we begin by situating eco-feedback research within HCI/Ubicomp (Section 2.1) and drawing a link to the field of information visualization (Section 2.2). We then review related work on the two environmental domains addressed in this dissertation: personal transportation and water usage. Section 2.3 provides work related to transportation sensing and feedback systems while Section 2.4 focuses on sensing and feedback systems for residential water usage. As noted in Chapter 1, a large portion of this dissertation is devoted to water (Chapters 6 through 9). Consequently, Section 2.4 begins with a broad review and background of water supply and usage including an argument for why residential water usage deserves attention and different strategies/approaches used by water utilities to control demand.

2.1 SUSTAINABLE HCI

The goals of this section are to help define and illuminate a still emerging area of research within Human-Computer Interaction (HCI) of which this dissertation is a part called “Sustainable HCI.” Broadly speaking, Sustainable HCI involves applying HCI methods, perspectives, and techniques to issues of environmental health and sustainability. As a still emerging area, there is debate about what constitutes Sustainable HCI and the research therein. To help contextualize and scope the research presented in this dissertation, I begin with a brief historical look at Sustainable HCI and summarize the state of the field.

Most attribute the emergence of "Sustainable HCI" as a subfield of HCI research to Eli Blevis' landmark CHI 2007 paper: *Sustainable Interaction Design: Invention, Disposal, Renewal & Waste*. Although other papers had previously considered the role of technology and environmental sustainability (*e.g.,* Jain and Wullert, 2002; Arroyo *et al.*, 2005; Friedman *et al.*, 2006), Blevis' work served as a catalyst to organize and formulate particular research agendas around environmental topics. In Blevis's paper, he argues that sustainability is inherent to HCI and claims that it should be a central focus of interaction design:

> *The focus [of this paper] is primarily on environmental sustainability and the link between interactive technologies and the use of resources, both from the point of view of how interactive technologies can be used to promote more sustainable behaviors and—with more emphasis here—from the point of view of how sustainability can be applied as a critical lens to the design of interactive systems themselves.*

Blevis' paper considers sustainability as core to interaction design—indeed, he defines design as "an act of choosing among or informing choices of future ways of being" (2007). From Blevis' perspective, a designer is centrally placed and perhaps ethically compelled to consider the environmental consequences of their design decisions because those decisions shape behavior. Although Blevis points to the role of interactive technologies in promoting sustainable behaviors (which is largely the focus of this dissertation) his primary focus is in discussing how sustainability can be applied to the design of interactive systems themselves. For example, he argues that designers should address the current movement towards creating technology for obsolescence, which creates a cycle of manufacturing and disposal that is harmful for the environment, rather than specifically using technology to persuade individuals to act more proenvironmentally.

Since Blevis' paper in 2007, Sustainable HCI has become one of the fastest-growing areas of research in the HCI and Ubicomp research communities. The subfield involves a variety of environmentally related topics including understanding home resource use and habits (Chetty *et al.*, 2008; Chetty *et al.*, 2009; Pierce *et al.*, 2010; Woodroof *et al.*, 2008), the design and evaluation of new resource consumption sensing technology (Patel *et al.*, 2007; Gupta *et al.*, 2010, Cohn *et al.*, 2010; Krumm Pervasive, 2011), and the exploration of tools to inform consumers about the environmental impact of their decisions (Tomlinson, 2008), to name a few. Such an upsurge in interest reflects both recent commensurate societal interest in environmental sustainability as well a movement within the research community itself to address high-value social topics through the lens of HCI (*e.g.,* aging in place applications and healthy living applications). Dourish (2010) summarizes this movement in the introduction to his DIS 2010 paper, which serves as a critical inquiry into Sustainable HCI:

> *Environmental sustainability has been one of the fastest growing areas of activity in HCI research in recent years. In part, this reflects the observation that pervasive information technologies provides a platform for reflection and intervention that may have positive social benefits. This observation has driven research in the use of information technology to promote personal health and wellness (e.g., Consolvo et al., 2008; Lin et al., 2006), as well, more broadly, as what some have termed "persuasive technologies" (Fogg, 2002). HCI research on sustainability is founded on the premise that global or environmental health and wellness might also be a site for similar technological interventions.*

The infancy of the Sustainable HCI field as well as its rapid growth has given rise to a number of papers, like Dourish's quoted above, that attempt to step back and critically reflect on where the field is going and where it has already been. In the first Special Interest Group (SIG) meeting on Sustainable HCI at the ACM Conference on Human Factors in Computing Systems, Mankoff *et al.* (2007a) uncovered two emergent categories of sustainability research in HCI: sustainability *in* design (*i.e.,* mitigating the material effects of software/hardware) and sustainability *through* design (*i.e.,* influencing sustainable lifestyles or decision making). This dissertation largely focuses on the latter category: achieving sustainability by creating awareness, informing decisions, and promoting proenvironmental behavior.

In a more comprehensive analysis of the Sustainable HCI literature, Goodman (2009), found that the vast majority of research fits under Blevis' definition of *sustainable interaction design*. However, she also identified two other research trajectories: (1) *re-visioning consumption,* which uses probes or critical art installations to examine how humans perceive their relationship with the world (*e.g.,* Bohlen, 2004; Paulos and Jenkins, 2006; Pierce and Paulos, 2010; Kuznetsov *et al.*, 2011); and (2) *citizen sensing,* which attempts to open and democratize science by allowing contributions through the use of mobile phones, sensors, and other emerging pervasive technologies. Eric Paulos and his Living Environments Lab at Carnegie Mellon University has been one of the more outspoken and prolific researchers in this area (see Paulos *et al.*, 2008b for an overview).

Partially inspired by Goodman's 2009 work, DiSalvo *et al.* (2010) also conducted a review of HCI sustainability research in attempt to "catalog the approaches and orientations that are being taken and to map out the differing intellectual commitments that underlie the area." From a literature review of 83 Sustainable HCI related papers, the authors identified five emergent, non-mutually exclusive genres, which are listed in Table 2.1. Of particular relevance here is the fact that DiSalvo *et al.* rescope the definition of *sustainable interaction design* to more accurately reflect the definition that has emerged in the HCI community since Blevis' original 2007 paper. Here, DiSalvo *et al.* use sustainable interaction design to mean "papers oriented around using sustainability as a critical lens to rethink the role and outcomes of design." This more limited definition not only better reflects the focus of Blevis' original paper (and those that cite it) but also enables the extraction/elevation of two other sustainability research areas ordinarily subsumed by Blevis' initial definition: *persuasive technology* (45% of papers) and *ambient awareness* (25% of papers). This distinction is of particular relevance to this dissertation because it more finely categorizes our own Sustainable HCI research pursuits, which fall under four of the five genres: persuasive technology (Chapters 3, 4, 5 and 9), ambient awareness (Chapter 5 and 9), formative user studies (Chapter 5, 6, and 9), and pervasive and participatory sensing (Chapter 5, 7 and 8).

Genre	Approximate Percentage of Corpus (N=83)	Description and Example Papers
Persuasive technology	45%	Persuasive technology is technology that is designed to persuade users to behave in a more sustainable way using either *strong persuasion* (*e.g.,* Bang *et al.*, 2006) or *passive persuasion* (*e.g.,* Gustafsson and Gyllenswärd, 2005; Gyllenswärd *et al.*, 2006).
Ambient awareness	25%	Ambient awareness systems draw upon notions of calm computing (Weiser, 1991) and ambient displays (Mankoff *et al.*, 2003) to make users aware of their behavior or qualities of the environment associated with issues of sustainability. The forms of these systems include: devices and physical artifacts (*e.g.,* Gustafsson and Gyllenswärd, 2005; Gyllenswärd, 2006), visualizations (*e.g.,* Holmes, 2007), instrumented environments (Bonnani, 2004), and intelligent agents (Al Mahmud, 2007).
Sustainable interaction design	10%	Describes papers oriented around using sustainability as a "critical lens" (Hanks, 2008) to rethink the role and outcomes of design; these works have often emerged from design research literature and are frequently philosophically and critically oriented (*e.g.,* Woolley, 2003; Blevis, 2007, Pierce, 2009)
Formative user studies	15%	Consists of studies to understand users' attitudes to the environment or to sustainable or unsustainable design. Methods include large-scale quantitative studies (Hanks *et al.*, 2008), qualitative interviews (Huang *et al.*, 2009) and ethnography (Chetty *et al.*, 2008; Woodruff *et al.*, 2008).
Pervasive & participatory sensing	22%	Work that involves sensors to monitor and report on environmental conditions with the implicit goal of using the data collected to change these conditions. Examples include systems to monitor food perishability in distribution networks (Ilic *et al.*, 2009), systems to monitor air pollution in homes (Kim and Paulos, 2009), or citizen science oriented works (*e.g.,* Foth *et al.*, 2008, Paulos *et al.*, 2008a; Paulos *et al.*, 2008b).

Table 2.1: A summary of DiSalvo *et al.*'s (2010) genre analysis of sustainable HCI topics. The work presented in this dissertation encompasses four of the five genres including persuasive technology, ambient awareness, formative user studies and pervasive and participatory sensing.

While the definitions and various categorizations of Sustainable HCI research offered by Blevis, Goodman, and DiSalvo *et al.* allow us think about and reflect on past, present, and future research agendas involving the environment and HCI, this is an evolving discourse of which my own work has played a role. Chapter 3 contributes specifically in terms of the role of HCI in the design and evaluation of eco-feedback technology. Before describing sensing and feedback work that specifically relates to the two core areas of this dissertation (transportation and water), the next subsection discusses how eco-feedback partially intersects with (and extends from) work in information visualization.

2.2 RELATING ECO-FEEDBACK TO INFORMATION VISUALIZATION

Eco-feedback systems are *visualization* systems. They visualize information about behavior that is otherwise latent or inaccessible. Card *et al.* (1999) define visualization as "… the use of computer-supported, interactive, visual representations of data to amplify cognition." We would argue that even eco-feedback systems that are text only (such as the Kill-A-Watt) are still visualization systems though they may not perfectly fit the Card *et al.* definition.

Historically, visualizations have been split into two major areas: "scientific visualization" and "information visualization" (infovis). The categorization of a visualization into one of these two areas is largely based on whether the application area is scientific or non-scientific, whether the data is physically based or abstract, or whether the spatialization[7] of the data is intrinsic or applied (Tory, 2004). Given this definition, eco-feedback systems would fall somewhere in the middle; the application area is primarily non-scientific in that the intended audience are everyday people without, necessarily, a technical background and yet the data is both physically based and has some underlying spatial component (making eco-feedback a candidate for scientific visualization). Recognizing the emergence of new types of visualizations such as eco-feedback that do not fall directly under either pre-existing category, Pousman *et al.* (2007) defined a new subdomain of infovis called: Casual Information Visualization (or Casual Infovis).

Casual Infovis is defined as "the use of computer mediated tools to depict personally meaningful information in visual ways that support everyday users in both everyday work and non-work situations" (Pousman *et al.*, 2007). Here, the purpose of infovis shifts beyond expert user populations and complicated interactive visualizations to everyday uses and user populations. In particular, Pousman *et al.* note four differences between traditional infovis and casual infovis:

[7] Spatialization refers to the *spatial* layout of data. Some data has an inherent spatial dimension such as that from Geographic Information System (GIS) or three-dimensional medical images. Other, more abstract data (*e.g.*, text documents) is not related spatially; however, spatialization (*e.g.*, graph layouts) can still be used to cluster and organize data.

- **User Population**: The user population is enlarged to include a broad spectrum of users from novices to experts. Users are not necessarily experts in analytic thinking or in reading visualizations.
- **Usage Patterns:** Usage extends past work to encompass all parts of life. The visualizations can be designed for momentary and repeatable usage (over weeks, months or years) or contemplative (long, thoughtful interactions).
- **Data Type:** The data is typically personally important and relevant as opposed to work-related, which means that a user's relationship with the data is often more tightly coupled.
- **Insight:** Card *et al.* (1999) define infovis as visualizations that intend to amplify cognition and provide insight. Pousman *et al.* (2007) argue that casual infovis systems provide insights that are different in kind and purpose from traditional systems. These insights include analytic insight, awareness insight, social insight, and reflective insight. Each of these insights are possible with eco-feedback systems.

Casual Infovis is useful to the design of eco-feedback because it, first, links eco-feedback to the discipline of information visualization and, as such, provides a useful vocabulary and research history with which to draw upon and, second, because it helps provide a design framework with which to approach the eco-feedback design process. We examine the eco-feedback design and evaluation process in more detail in Chapters 3 and 4, both of which also refer to work conducted in information visualization.

We now turn towards examining related work specific to the areas of sensing and feedback for personal transportation and for water usage. As water takes on a larger role in this dissertation, these sections reflect this emphasis proportionally. We also note that a more general review of eco-feedback in HCI and in environmental psychology can be found in Chapters 3 and 4.

2.3 TRANSIT SENSING AND FEEDBACK

We now transition to describing the related work for the sensing and feedback artifacts we created and present in Chapters 5, 7, 8 and 9. The work described in this section is directly relevant to UbiGreen, the sensing and feedback system for personal transit routines presented in Chapter 6. The next section (Section 2.4) describes work relevant to water usage sensing and feedback systems.

2.3.1 Transit Sensing

Sensing and inferring human context such as activity, location and movement has long been a goal of Ubicomp research. Sensing and inferring transportation modes intersects with all three of these in that *location* and *movement* are often used to derive the user's transit *activity*. Given that this dissertation is not offering transportation sensing as a primary contribution, this related work section will be brief in comparison to the water sensing section. In addition, although algorithmically our approach to inferring a user's transit mode is rather simple, the key differentiator from past work is the way in which we integrate multiple sources of data from a wearable sensor, cell towers, and user self-report. Our focus here, then, is predominantly on sensing methods for inferring transportation modes rather than a deep review of the classification algorithms used to do so.

There have been two primary application drivers for sensing and inferring transportation modes: *physical activity monitoring* (*e.g.,* Consolvo, 2008) and *eco-feedback systems* (*e.g.,* Mun *et al.*, 2009). As Reddy *et al.* (2010) note, both of these areas require high accuracy from the underlying transit mode classification system. For example, in an application such as UbiFit, designed to track and encourage fitness activities (Consolvo *et al.*, 2008), automatically classifying a run as a bicycle ride or motorized transport could significantly affect caloric expenditure estimates and undermine user confidence in the application. Similarly, for eco-feedback applications, offering CO_2 emission estimates and recommending appropriate alternative transit is contingent on the underlying sensing and inference system being able to track vehicle usage versus alternative, more environmentally friendly forms of travel. Defining "high accuracy" in these contexts is an open research area and is dependent on a specific application's needs. Reddy *et al.* (2010) stipulate that in order for their Personal Environmental Impact Report (PEIR) system to perform appropriately, transit mode classification accuracy has to be above 90% (Mun *et al.*, 2009). For UbiGreen, we did not empirically test and validate the accuracy of our hybrid sensing approach (though our techniques were primarily based on vetted algorithms from Lester *et al.*, 2006 and Sohn *et al.*, 2006). Instead, we simply allowed the user to self-report transit activities to compensate for inaccurate or unavailable transit inference.

Four sensing techniques are commonly used to sense a user's transit mode: (i) beacon-based sensing (LaMarca *et al.*, 2005); (ii) GPS-based sensing (Zheng *et al.*, 2008); (iii) body-worn or "wearable" sensing (Parkka *et al.*, 2006); or a (iv) hybrid approach that incorporates more than one of the previous three techniques simultaneously (Lester *et al.*, 2008). Each of these approaches varies in complexity, power requirements, and user burden (*e.g.,* wearable sensors require that the user remembers to wear the sensor and that s/he is able to properly place it on his/her body). UbiGreen employs a hybrid approach to tracking users' transportation modes. This includes a wearable sensing system, the Intel Mobile Sensing Platform (MSP) (Lester *et al.,* 2005; Choudhury *et al.,* 2008), for inferring physical activities such as walking, running, and bicycling as well as beacon-based sensing and user self-report to track vehicle driving, bus riding, and train riding. It is important to note that UbiGreen was developed and evaluated in 2007 and 2008. At the time, there were few published works on automatically identifying and discriminating a user's transit mode, and even then, most of this research was evaluated on a relatively small scale. In addition, although the mobile phone has long been touted as the ideal platform for sensing and inferring physical human activity, only recently have mobile phones begun to integrate sensors such as accelerometers, GPS, and gyroscopes, which are important to activity inference systems. In 2007, these sensors were not available within the mobile phone itself and thus required an external wearable sensing platform. Below, we review the transit sensing and inference literature organized around the three approaches: (i) beacon-based sensing; (ii) GPS-based sensing; (iii) wearable sensing.

2.3.1.1 Beacon-Based Sensing

Beacon-based location sensing systems rely on *fingerprinting* ambient radio signals to infer a user's location (Bahl and Padmanabhan, 2000; Krumm *et al.* 2003; LaMarca *et al.*, 2005, Varshavsky *et al.*, 2007). Unlike GPS-based sensing, which provides geographic coordinates (*e.g.,* latitude and longitude) to locate a user's position, beacon-based sensing systems must use a pre-existing lookup table to translate the sensed radio signals ("fingerprints") into geographic coordinates. For example, in Placelab (LaMarca, 2005), WiFi Service Set Identifier (SSID) codes along with signal strengths are used by clients to lookup the location of these beacons in a locally cached map and estimate their own position. This process, of course, requires that fingerprints for these beacons exist in the lookup table and that the beacons' physical, geographic locations are known. If geographic coordinates do not exist for those fingerprints in the lookup table, the user's location is returned as unknown. In the past, these lookup tables were constructed by "war-drivers" who would drive around cities with GPS receivers and upload the coordinates of the radio fingerprints. Now, with the widespread availability of GPS in phones and other devices, these lookup tables are often built automatically and dynamically over time.

Before large-scale adoption of GPS in mobile phone devices, beacon-based sensing was cast as the cheapest and easiest way to determine a user's position (LaMarca *et al.*, 2005). However, even in modern smartphones, beacon-based sensing is still used because of its ability to work indoors, in urban canyons, and because it can use less power than GPS. Companies such as Skyhook Wireless[8] provide commercial APIs for translating sensed WiFi beacons (SSID codes and signal strengths) and

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[8] http://www.skyhookwireless.com/

cell tower beacons (a GSM cell id and signal strengths) into location data. These sorts of services are used in Apple iPhone and Google Android devices to provide a layered, hierarchical location system that relies on a combination of GPS, WiFi, and cell tower signals to achieve the greatest location accuracy depending on signal availability.

In addition, depending on what type of human activity/location inference is required, geographic coordinates can be unnecessary. For example, beacons can be used to track time spent in a location or to recognize when a user arrives at a location that s/he has been at before (Hightower *et al.,* 2005). Note that "location" here does not mean *geographic* location but rather a unique radio signal fingerprint location (a "virtual" location in the physical world). Along similar lines, beacon-based sensing has also been used to infer a user's motion (Krumm, 2004) and even transportation modes (Sohn, 2006). UbiGreen builds off work by Sohn *et al.* (2006) by utilizing cell tower radio information to infer the user's transit mode. However, whereas Sohn *et al.* relied solely on cell tower signals, we also incorporated data from a wearable sensor (the MSP) and user self-report. In addition, algorithmically, Sohn *et al.* utilized cell tower ids and differences in signal strengths to classify motion into four discrete categories: stationary, walking, fast walking and vehicle transit. In our case, because the MSP provided activity classification estimates for stationary, walking, running and bicycling, we relied on the cell tower signals to distinguish vehicle-based transit (*i.e.,* fast motion) from these slower modes of movement. In addition, rather than focusing simply on the differences in cell tower strengths over time, we also specifically incorporated the rate-of-change of the seven visible cell towers seen by the phone into our classification algorithm. A similar approach was taken by Mun *et al.* (2008) but they monitored the rate-of-change of only a single connected cell and complemented this with WiFi beacon data.

2.3.1.2 GPS-Based Sensing

With the increasing prevalence of GPS in mobile phones and consumer electronics, GPS-based activity recognition has received considerable research attention including using GPS streams to extract and identify an individual's significant places (*e.g.,* their home, their work) (Ashbrook and Starner, 2003; Liao *et al.*, 2005), to predict a person's movement or destination (Patterson *et al.*, 2003; Krumm, 2006; Froehlich and Krumm, 2008) and to model and infer a user's transportation mode (Patterson *et al.*, 2003; Liao *et al.*, 2004; Zheng, 2008). For example, Patterson *et al.* (2003) used GPS tracks to classify a user's mode of transportation as either "bus", "foot", or "car", and to predict his or her most likely route. However, GPS was not available as an embedded sensor within mobile phones at the time we created UbiGreen and thus not used by our system.

2.3.1.3 Wearable Sensors

In contrast to beacon-based or GPS-based sensing approaches which are often mediated through a mobile device such as a phone, wearable sensors require that the user "wear" a sensor (or sensors) to infer human activity. Although potentially burdensome to the user, the benefit is often higher classification accuracies and more fine grain sensing than the previous two approaches. In UbiGreen, users wore the MSP on their waist. The MSP is a pager-sized device that combines an Intel XScale processor with an accelerometer, barometric pressure sensor, light sensors, humidity sensors, and microphone (audio was not used in UbiGreen) to infer a set of trained human activities such as walking, stair climbing, or running. In laboratory studies, the MSP was capable of classifying sitting, walking and jogging and riding a bicycle at rates of above 90% when trained on a total of ten activities (Lester *et al.,* 2005). For UbiGreen, we trained the MSP to recognize stationary, walking, running and bicycling activities. In addition to UbiGreen, the MSP has also been used in projects tracking and supporting health and wellness (Consolvo *et al.*, 2004; Consolvo *et al.*, 2008; Denning *et al.,* 2009) and to categorize how human activities relate to space (Lester *et al.*, 2008).

Other relevant wearable sensing work for determining human transit activities includes Farringdon *et al.* (1999) and Randell and Muller (2000), who have created systems that use a single accelerometer to infer stationary, walking, and running activities. Researchers have also looked at using multiple sensors placed at different positions on the body to improve recognition accuracies (*e.g.,* Bao and Intille, 2004; Saponas *et al.*, 2008). Recently, specialized commercial devices are emerging for sports and fitness tracking. The FitBit[9] and Phillips DigitalLife[10] sensors incorporate multi-axis accelerometers to provide a convenient (orientation agnostic) method to infer coarse-grained activity levels (*e.g.,* sedentary, active, vigorous). Although these commercial offerings are cheap and convenient, they do not attempt to infer a user's particular activity or transit mode.

2.3.2 Transit Feedback

Although there has been considerable research attention applied to activity recognition and transit mode inference, much less work exists around building actual applications on top of these inference systems. This both speaks to the remaining challenges in reaching high classification accuracy levels

[9] http://www.fitbit.com/
[10] http://www.directlife.philips.com/

to enable these applications (as noted by Reddy *et al.*, 2010) as well as the difficulty in building and evaluating these applications in the field. More than 2.5 years have passed since the publication of UbiGreen (Chapter 5), and, to our knowledge, no other systems have emerged that track and feedback information about a user's various transit routines from walking to vehicle-based transit. However, UbiGreen is just one of a long line of information technologies built to support alternative transit decision making. We review these tools below.

OneBusAway (Ferris, 2010) is a web- and phone-based transit tool that provides real-time arrival information for bus riders. Ferris *et al.* showed that OneBusAway users were more satisfied with public transit, experienced decreased waiting times, and had increased feelings of safety while waiting for the bus. WalkScore is a website that calculates the "walkability" of cities and neighborhoods based on proximity to amenities in nine different categories including grocery stores, restaurants, parks, schools, cafes, and libraries. Whereas OneBusAway is meant to provide real-time bus transit information to city residents in order to inform their transit choices *in situ*, WalkScore is meant as a planning tool to help people decide where to live and for city planners and governments to make improvements on land use. Tools like OneBusAway and WalkScore are complementary to UbiGreen; UbiGreen could be improved, for example, by having better *decision support* to help people make greener choices. UbiGreen could recognize that a bus route exists for a user's commute route and explain the costs/benefits of taking the bus versus driving in terms of time, money, and the environment.

While the tools above are useful to inform and support greener transit decisions, they are not particularly useful once the user has already decided to drive or is already in the car. A large body of research exists around feedback interfaces to support "eco-driving"—that is, driving that is non-aggressive, smooth, and avoids rapid acceleration. Past work has shown that drivers could reduce fuel consumption by ~15% without increasing trip time simply by reducing acceleration levels and driving more gently (Evans 1979; Waters and Laker, 1980). Van der Voort *et al.* (2001) applied these findings to create one of the first systems that automatically measured driver behavior and fed back information and suggestions to encourage more fuel efficient driving. Since then, a number of researchers in HCI and transportation research have investigated in-car dashboard displays to change driving behavior in order to increase fuel efficiency (Adell, 2008; Graving *et al.*, 2010; Kim, 2011; Larsson, 2009). Many elements of these systems are now in modern vehicles such as the Toyota Prius, Ford Smart Gauge, and Mercedes-Benz BlueEfficiency fuel economy display. For a full review, see these two reports by the Department of Transportation: *Fuel Economy Driver Interfaces: Design Range and Driver Opinions* by Jenness *et al.* (2009) and *Fuel Economy Driver Interfaces: Develop Interface Recommendations* by Manser *et al.* (2010). A slightly different approach was taken by Ganti *et al.* (2010), who created a system called GreenGPS that recommended the most fuel efficient routes to a particular destination (based on user contributed onboard diagnostic OBD-II data). GreenGPS and the interfaces focused on influencing more fuel efficient driving behaviors could work in tandem.

In summary, to our knowledge, no tools exist that sense and feedback information about transit routines in order to promote greener decisions. However, the other tools covered in this section could be integrated into future UbiGreen designs (*e.g.,* by integrating personalized suggestions about alternative transit opportunities based on sensed routines).

2.4 WATER

We transition now from work related to sensing and feedback for personal transportation to water. Before we discuss specific relevant water sensing and feedback techniques in particular, we first provide background on water as a resource, the hydrologic cycle and existing approaches to water demand management. Although such work falls outside the scope of traditional HCI and Ubicomp research, it is directly relevant to the design of water-based eco-feedback systems as it provides motivation, scope, and context. As we have argued previously (Froehlich *et al.,* 2010), it is critically important for eco-feedback designers/researchers to educate themselves in the environmental domain related to their target behaviors.

2.4.1 Water Consumption Background

Water is the most common substance on earth—two-thirds of the earth's surface is covered by water. Less than one percent of this, however, is drinkable: roughly 96.5% is ocean water, 1.7% is frozen in polar ice, and 1% is too brackish to drink, which leaves 0.8% in lakes, rivers, wetlands, in the ground and in the atmosphere (Glennon, 2009). Although these percentages can change, the total amount of water on earth is fixed—neither growing nor shrinking (Gleick, 2009). As Glennon notes, "We are drinking the same water that dinosaurs did" (2009). The amount of water on earth is not changing, but its location, quality and amount per person *is* changing. As populations grow, per-capita water availability is declining. And, as the world's climate changes, so too do precipitation patterns, glacial and ice snowpack, and the availability of surface water, which will greatly impact traditional water supply sources and further increase the cost of finding new ones (Gleick, 2009). Moreover, while water scarcity is a global problem, it is felt most acutely on the regional level. This is because water, unlike energy, is difficult to transport. Thus, those cities that are experiencing rapid population influxes and growth in industries are often struggling to meet new water demand. And, what's worse, many of these newly thriving regions have traditionally had limited access to freshwater: cities like Las Vegas, NV and Beijing, China.

2.4.1.1 Water as a Resource

Before discussing where water comes from, where it goes, and the role that residential consumption plays in this hydrologic cycle, it is worth delineating the ways in which water is a unique resource. This differentiation is useful both to emphasize its value to us as humans as well as to highlight particular characteristics not found in other home resources such as electricity and gas, which have largely been the focus of much past eco-feedback research (as we note in Chapter 3 more specifically).

Water is a unique natural resource with a combination of characteristics that differentiate it from any other good. (1) *Water is essential*. Water is a fundamental ingredient of life—without water, there is no environment, there is no life. As Savenije (2002) notes, "there is no human activity that does not depend on water." (2) *Water has no substitutes or replacements.* Unlike the energy supplied to our homes, which can be derived from multiple sources (*e.g.,* solar, nuclear, coal, hydroelectric), there is only one water. (3) *Water cannot be produced or manufactured*. Currently, there are no economically viable methods to produce water. Desalination, which is often cited as a way to "manufacture" water, does not produce new water but rather converts salt water to fresh. However, desalination is extremely energy intensive and expensive and currently constitutes less than three one-thousandths of the US water supply (Glennon, 2009). (4) *Water is difficult to transport and convey* making it expensive to geographically shift large quantities. (5) *Water moves*—unlike other resources, water flows and is unequally spread in space and time, making water plentiful in some regions and scarce in others. In addition, this movement makes water difficult to divide for equitable use as it flows across geo-political boundaries (Clarke, 1991). Finally, (6) unlike other resources such as electricity and gas, the water supplied to buildings is not consumed—just transformed and contaminated, which requires its own infrastructure to move away from buildings and treat. The preceding list was largely compiled from Grimble (1999), Savenije (2002) and Blanksby (2006) (exceptions noted with particular citations).

2.4.1.2 Consumptive versus Non-Consumptive Use

An additional difference not noted above, which deserves its own subsection both because of its complexity as well as its relation to residential consumption, is that water is, rather remarkably, both a "renewable" and "non-renewable" resource. We do not destroy water when we use it; we simply change its character and its location (Glennon, 2009). When farmers water their fields, the crop absorbs some water, some water evaporates into the atmosphere, some of the crop's leaves emit water into the atmosphere via transpiration, and some percolates into the ground eventually reaching aquifers (Glennon, 2009). As Glennon (2009) states, "This hydrologic cycle begs an important question: if our water supply is fixed and we can neither make nor destroy water, how can we run out of it?" The answer lies in what water scientists distinguish as "consumptive" vs. "non-consumptive" use.

A consumptive use of a resource is one that expends or transforms a resource such that it can no longer be used. Practically every use of petroleum, for example, is consumptive; once the energy is extracted and consumed, it is no longer usable (Gleick, 2010). Water is different. Consumptive uses of water make water unavailable for immediate or short-term reuse—for example, within the same watershed. Consumptive uses of water include that which has been evaporated, transpired, incorporated into products or crops, heavily polluted, or consumed by humans or animals (Gleick, 2010). In the domestic sector, outdoor water usage is largely consumptive as is the water used for drinking and cooking (Gleick *et al.*, 2008; Vickers, 2001). In all, about 100 billion gallons of water are used *consumptively* by irrigation, industry, and residential sectors each day (Gleick, 2001a).

There are also many non-consumptive uses of water. The water used for cooling in the thermoelectric power industry, for example, is mostly non-consumptive. In the domestic sector, water that flows down the drain—*e.g.,* water used for washing or flushing—is non-consumptive but only if the sewage water is properly collected and treated (Gleick, 2010). In addition, depending on the source and location of the water supply, even non-consumptive uses of water can become consumptive. Glennon (2009) provides the example of municipalities near coastal areas that pump groundwater, deliver it to residents, treat the resulting sewage, and dump the treated water into the ocean. This once potable freshwater then becomes unavailable for use until it evaporates off the ocean, infiltrates the ground, and percolates into an aquifer, where it can be pumped back into the water supply by the municipality (this process may take from years to centuries (Winter *et al.*, 1998)). Thus, water scarcity is often a function of timing and location, which is compounded by growing population and demographic shifts (Glennon, 2009). Given this distinction, where does our water come from, where does it go, why is it abundant in some places and scarce in others, and what role does residential water consumption play?

2.4.1.3 Where Does Our Water Come From and Where Does it Go?

In the United States, freshwater makes up 85% of all water withdrawals—the remaining 15% is saline water mostly used to cool thermoelectric power plants (U.S. Geological Survey, 2011). Of all the freshwater in the world, 68.7% is locked up in glaciers and icecaps, 30.1% is ground water and just 0.3% is from surface water such as lakes and rivers (U.S. Geological Survey, 2011). Most of the water we drink comes from these surface water sources—which can be overdrawn or polluted leading to water scarcity.

On average, about 410 billion gallons of water per day (Bgal/d) are withdrawn for use in the United States. As shown in Figure 2.1, the top three water use categories comprise 91% of this daily average: thermoelectric power (49%), irrigation (31%) and public supply (11%). However, water use by thermoelectric power plants is for cooling and is largely *non-consumptive*, since nearly all of the large volumes of water withdrawn are returned to the source (albeit with some environmental consequences, *e.g.,* thermal pollution). Agriculture comprises 31% of water withdrawals in the US (behind thermoelectric), but it is the number one consumer of water worldwide (Gleick, 2001b).

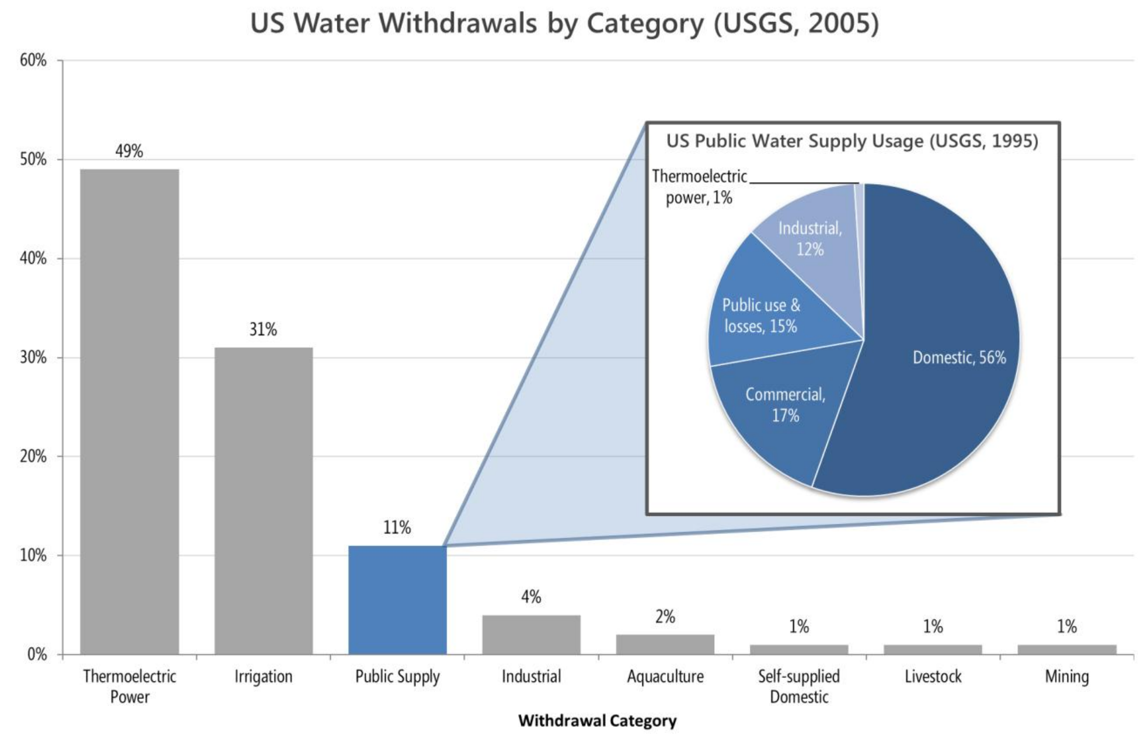


Figure 2.1: Water withdrawals by category in the United States. The US Public Supply accounts for 11% of total use, 56% of this is domestic. Self-supplied domestic (*i.e.*, well water) is its own category and accounts for 1% of total water withdrawals. Altogether, domestic water accounts for the third highest use in America (~7%).

The focus of this dissertation is largely on domestic or residential use, which falls under two categories: public and self-supplied domestic (*e.g.,* well water). Approximately 258 million people rely on public water supply for their household use (86% of the US population); the remaining 14% (42.9 million people) supply their own water (*e.g.,* via wells) (Kenny *et al.*, 2009). The domestic sector is not the only user of public supply water, but it is the largest user (56%). These percentages vary from state to state based on local economies and population demographics. For example, Iowa's domestic sector accounts for only 40% of publically supplied water (the minimum amount across the US) while Maryland's domestic sector uses 79% (the maximum). Following the domestic sector, the industrial, public use[11] and commercial sectors comprise 12%, 15%, 17% respectively of total public supply use. Overall, public supply water represents about 13 percent of total freshwater withdrawals in the US and 21 percent of all withdrawals not including thermoelectric power (Kenny *et al.*, 2009).

[11] *Public use* should not to be confused with *public supply*. Public use is a type of public supply use, which encompasses water use from pools, parks, and municipal buildings as well as water used in wastewater treatment.

The above data is heavily focused on water use patterns in the US. Water use is highly regionalized and depends on socioeconomics factors, population densities, amount of available arable land, local industry and countless other factors (see Chapter 6). In Europe, for example, the residential sector accounts for a significant portion of freshwater withdrawals from surface and ground water sources. Domestic water use accounts for an average of 25.3% of freshwater withdrawals with variation ranging from 3% in Bulgaria to 78% in Lithuania (Gleick *et al.*, 2008). In Nigeria, residential water consumption accounts for 80-93% of total water consumption (Jeffrey and Geary, 2006).

According to the USGS (Kenny *et al.*, 2009), overall water usage in the US has actually declined from peak levels in the late 1970s and early 1980s. Most of this decline has come from thermoelectric power and irrigation, the two largest uses of water, which have largely stabilized or decreased since 1980. The reduction in thermoelectric and irrigation use is likely due to increased costs of water, reduced water availability, and changes in technology, which have improved water efficiency. However, withdrawals for public-supply and domestic uses have steadily *increased* since the USGS started collecting data in 1950.

2.4.2 Why Residential Water Use?

Although domestic water consumption is a relatively small portion of overall water use in the US (Kenny *et al.*, 2009), water research scientists argue that it warrants close attention. Peter Gleick, one of the world's preeminent scientists working on global water issues and a MacArthur Fellowship award winner, is also the author of a respected biennial report on water called *The World's Water* (Gleick *et al.*, 2006; Gleick, *et al.*, 2008). In the 2006-2008 edition, Gleick *et al.* (2006) note that municipal water supplies are critically important because they are traditionally the primary drivers for new water acquisitions and require significant capital expenditures to build and maintain water infrastructure. Gleick *et al.* also note that in the western United States, where water is scarce and largely allocated, new sources of water can be difficult to obtain for domestic use and those that can be obtained have high costs—both economically and environmentally. Consequently, he recommends, municipalities need to identify ways of using existing water resources more effectively rather than finding new supplies. Figure 2.2 shows the variations in domestic per capita water use by state—note the wide variation in use from Nevada (190 gallons) to Maine (54 gallons) and the concentrations of high use in the western and southern parts of the United States.

With overall increases in population and more homes being built, the demand for domestic water across the world is increasing (Strang, 2004). Global population will reach 7 billion sometime in 2011, just 12 years after reaching 6 billion. Today's world population is double the population in 1967 (Population Reference Bureau, 2011). Although the overall population growth rate has recently slowed, the population is still growing, and growth rates in some countries show little if any decline (Population Reference Bureau, 2011).

Increased water demand from growing population is not the only problem; the concentration of populations in urban areas is exacerbating the issue. For example, between 1950 and 1990 the number of cities with populations of more than 1 million increased from 78 to 290 and this is expected to exceed 600 by 2025 (Serageldin, 1995). This population growth in cities is not simply due to lower mortality rates or higher birth rates. Instead, much of it is due to migration of the rural population to urban centers. In 2006, for the first time in history, the number of people living in cities surpassed the number of people living in rural areas (Barlow, 2007). And, unfortunately, many people are migrating from where there is water (*e.g.,* the Midwestern United States) to where there isn't (*e.g.,* the Southwestern United States) (Glennon, 2009).

The southwestern region is of particular concern in the United States. The growth rates are so high in many southwestern cities that projections indicate some areas will see demand exceed supply by 2025 (Campbell *et al.*, 2004). Between 1920 and 2000, for example, population growth in the seven states that share the Colorado River grew nearly 800%; today, the Colorado River basin is home to 50 million people, 92% of which live in urban areas. This is expected to grow to 73 million people by 2030 (Gober and Kirkwood, 2010). What's worse, these areas tend to use the most water because their arid climates cannot support lawns and gardens from precipitation alone. Many regions across the world are facing similar scenarios.

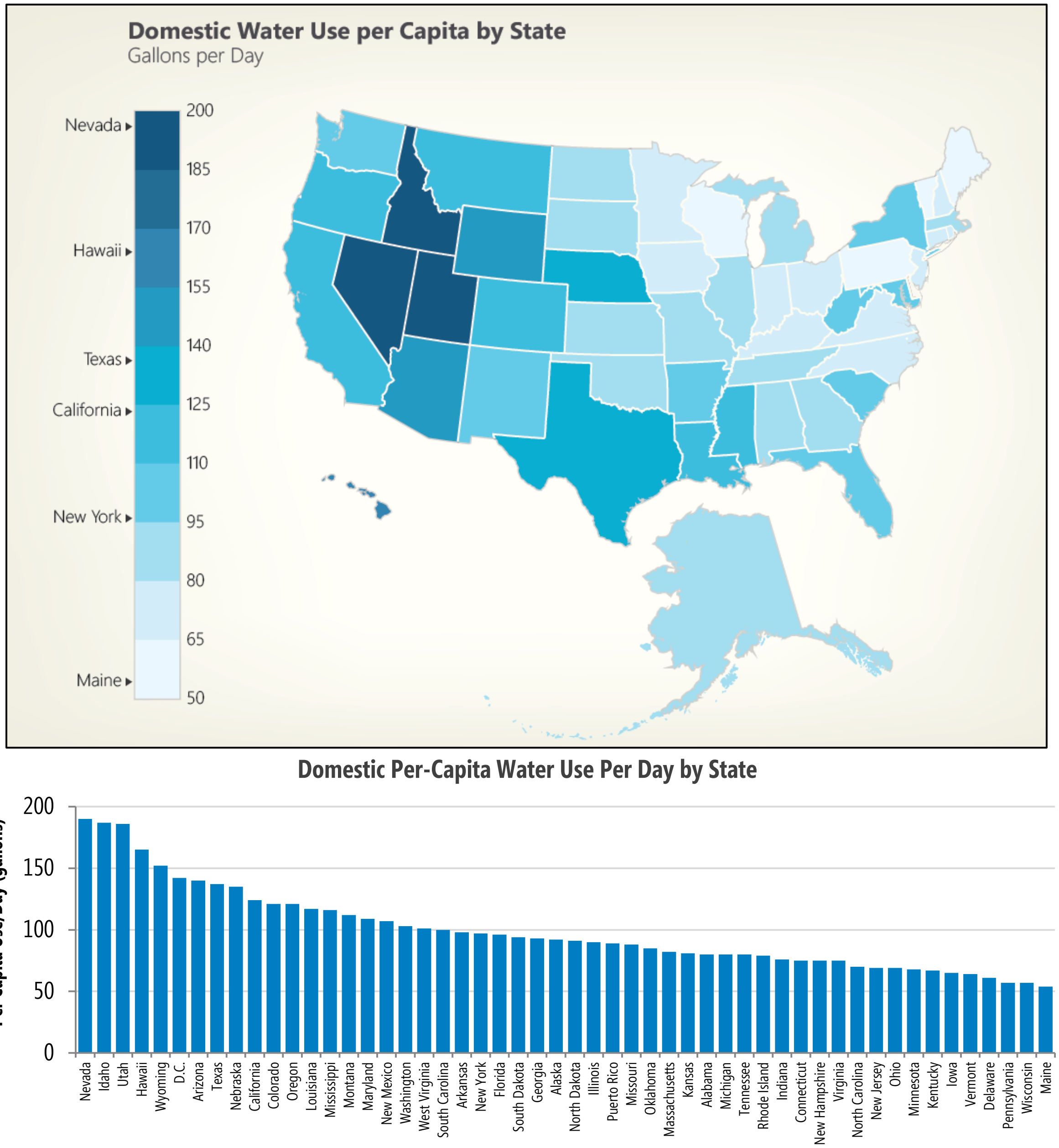


Figure 2.2: Total domestic per capita water use in gallons per day by state (includes both self-supplied and public supply). Data from Kenny *et al.* (2009).

China, for example, is home to 21 percent of the world's population but has just 7 percent of the world's water (Lippert and Efstathiou, 2009). Last year, the government in Beijing, a city long faced with water shortages, began melting snow with high-powered heaters to provide potable water to its population of nearly 20 million and growing (PhysOrg, 2009). Such drastic government involvement is not just common in developing countries. In 2008, Barcelona, Spain and its metropolitan region suffered one of the worst water crises of the last 50 years. Low rainfall in 2007 had caused a dramatic decrease in the water stored in the local reservoir system (Domene and

Sauri, 2006). Consequently, the local government began importing water by tanker ship at a cost of $35 million per month to meet domestic water demand (which represents over 65% of total consumption in the area) (Corbella and Pujol, 2009; Crawford, 2008).

The United States is not immune to such water shortages either—thirty-five of the lower forty-eight states are embroiled in water disputes (Glennon, 2009). Las Vegas, one of the fastest growing cities in the US, is built in the middle of a desert. Lake Mead, which supplies 40% of Las Vegas' water, is estimated to drop below intake pipes in the next five years (Lippert and Efstathiou, 2009). The water authority in Las Vegas is going to unprecedented lengths to promote water conservation, including paying people to replace their lawns with desert-friendly landscape (*i.e.,* xeriscaping) up to $300,000 per year (City of North Las Vegas, 2011). And, although the Southwestern US is the most water stressed region, other parts have suffered from water shortages. In 2007, the town of Orme, Tennessee ran out of water due to drought (Glennon, 2009; Associated Press, 2007). The city of Orme began trucking its fresh water in from Alabama. The town was supplied with water between 6 and 9 every evening.

> "You never get used to it," says Cheryl Evans, a 55-year-old who has lived in town all her life. "When you're used to having water and you ain't got it, it's strange. I can't tell you how many times I've turned on the faucet before remembering the water's been cut."
>
> "You have to be in a rush," she says. "At 6 pm, I start my supper, turn on my washer, fill all my water jugs, take my shower."

Thus, it is of critical importance that domestic water be used efficiently. Unfortunately, this is not often the case—people are typically unaware of their consumption patterns and the affects this consumption has on the environment. The following example provided by Hadhazy (2008) illustrates this rather well: In 2007, Atlanta was suffering from one of its worst droughts in a century; a large home owned by a wealthy businessman consumed 440,000 gallons of water in one month alone. After public outcry (including newspaper stories calling him out directly), the property reduced its monthly usage to 12,000 gallons a month—about what an average US family of four consumes during the same period. Although admittedly this is an extreme case, it demonstrates first that there is a lack of awareness about water usage and that water usage can be reduced with some form of intervention such as eco-feedback systems.

2.4.3 Water Management Programs and Strategies

Historically, water management policies have focused on meeting demand through increased supply: build large-scale, government subsidized infrastructure to provide water to growing populations (Gleick, 2010). These policies were seen as necessary to support and encourage population expansion and economic growth, yet they tended to encourage infrastructure with excess supply and quality for many routine uses, such as toilet flushing and garden watering (Jeffrey and Geary, 2006). Vairavamoorthy (2006) and others (*e.g.,* Gleick, 2010) cite this supply oriented approach as a reason why there has historically been limited innovations in demand management and water conservation. Attempts to restrain or qualify water use either through fiscal, legislative, or technological means, have usually only played a role in times of drought events (Jeffrey and Geary, 2006). However, as many of the most accessible water sources in cities have already been developed, the cost of developing new sources or expanding existing ones is increasing (Vairavmoorthy, 2006). This has resulted in large scale efforts by water suppliers and governments to introduce *Demand Side Management* (DSM) campaigns to curb excessive use and create a more efficient water delivery infrastructure. These campaigns usually involve a combination of approaches including economic incentives and disincentives, regulatory policies, education and voluntary action (Inman and Jeffery, 2006; Gleick *et al.*, 2008, p106).

Before reviewing these approaches in more detail, it is useful to provide some background on water usage rates in North American households. For example, what's a reasonable amount of water usage per capita and what sort of target should water suppliers set for their efficiency goals? As we saw in the previous subsection, water usage is highly regionalized and dependent on a number of socioeconomic and cultural factors (these are reviewed in more detail in Chapter 6). However, setting these dependencies aside, scientists have attempted to calculate the minimum water usage requirements for humans including drinking, cooking, bathing and sanitation. Maude Barlow, the author of *Blue Gold* (Marlow and Clarke, 2002) and *Blue Covenant* (Barlow, 2007) and a staunch advocate of water as a political and social right, calculates a "water lifeline" at 6.5 gallons per day. Gleick (1998) argues that it takes a minimum of 13 gallons of water per day per person.

To place these numbers in context, Las Vegas, NV uses 165 gallons per capita per day, Atlanta, GA, 91 gallons, and Seattle, WA, 63 gallons (Figure 2.3). The national average is 101 (Vickers, 2001). We are not advocating that eco-feedback or other conservation management strategies should aspire to the minimum usage rages (*e.g.,* 6.5 gallons per capita per day), but these numbers do serve to highlight the disparity between necessity and comfort and, perhaps, the differences that are due both to context (*e.g.,* local climate) and behavior. Vickers (2001) offers a more reasonable goal of 43-45 gallons per capita per day for a water efficient household.

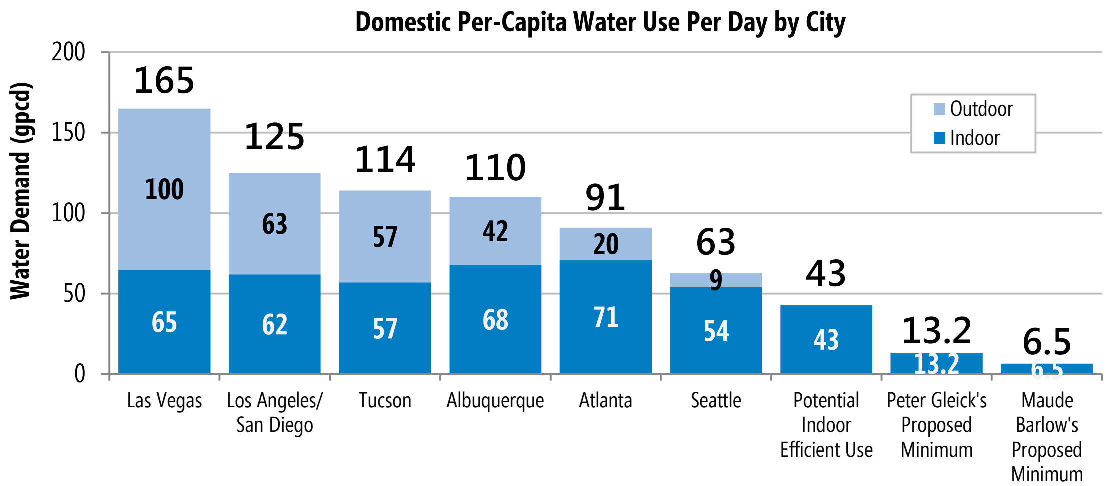


Figure 2.3: Domestic per capita water use in gallons per day by city. Data for Las Vegas, Los Angeles/San Diego, Tucson, and Albuquerque from Cooley (2007); data for Seattle, Atlanta and "Potential Indoor Efficient Use" from Gleick *et al.* (2008); the rest of the data is from Glennon (2009, pages 174 and 230).

With these estimates providing a target for efficient use, we now turn towards our brief review of DSM programs. These programs are split between *non-pricing* and *pricing* strategies. Eco-feedback would traditionally fall under the former category; however, it could also be used to provide residents with information on time-of-use pricing and other cost information, which intersects with the latter category. We discuss both strategies in turn.

2.4.3.1 Non-Pricing Strategies

Due to political opposition, equity concerns, legal limitations and a host of other reasons, water utilities are frequently reluctant to rely completely on price to control for demand (Kenney *et al.*, 2008). Thus, the following strategies are often implemented in conjunction to produce both temporary (*e.g.,* drought-motivated) and permanent reductions in consumption. These strategies are generally grouped into three categories: educational, legislative, and technological—however, all three interact together in some way.

Educational

Research into educational programs and informational campaigns has found that they can be modestly successful, particularly in the short-term (Michelsen *et al.*, 1999; Syme *et al.*, 2000). These educational programs tend to be implemented via flyer inserts in bills, radio or television spots (particularly during droughts), school visits, residential audits, or the use of other media (*e.g.,* billboards) (Michelsen *et al.*, 1999). In a literature review of the effects of informational campaigns to promote household water conservation, Syme *et al.* (2000) note that there are few formal evaluations of such campaigns on water use and most that do exist, are short-term evaluations used during drought situations. In both of their literature reviews, Michelsen *et al.* (1999) and Syme *et al.* (2000) show that educational/informational campaigns can be successful but that it is difficult to tease out statistical significance attributable to these campaigns because of confounding factors.

As we note in Chapter 3 and 4, eco-feedback, in general, can educate the consumer by providing active feedback for usage amounts and patterns that are otherwise latent and inaccessible. An eco-feedback system could also incorporate “tips” or educational materials more explicitly in the display, which could be personalized to the consumption habits sensed in the home (*e.g.,* “it seems as though you regularly water the lawn during mid-day, it would be much more efficient if you watered in the morning or evenings”). In Chapter 9, we discuss how one emergent theme in reactions to our eco-feedback displays was oriented around their educational potential, particularly for children to learn about resources in the home and concepts around conservation.

Legislative

Legislation can be used to reduce water use through mandatory or voluntary restrictions, to mandate new plumbing codes, and to mandate new fixture/appliance efficiency measures. The literature is consistent in showing significant (sometimes 30% or more) savings from mandatory restrictions (*e.g.,* outdoor lawn watering programs); however, findings from voluntary restrictions are much more variable. See Kenney, 2008 for a review.

In the United States, the Energy Policy Act of 1992 (H.R.776, 1992) mandated improved water use efficiencies for fixtures such as toilets, faucets and showerheads. More recently, the US EPA has sponsored the WaterSense program[12], which is not a *regulatory* program but rather a voluntary program for manufacturers to meet some threshold of water efficient performance. Manufacturers that meet these requirements are able to use the WaterSense label on their product (this is similar to the EPA’s Energy Star program for electronic device efficiency[13]). Such programs have been greatly successful in reducing use as we describe in the Technological Measures subsection next.

[12] http://www.epa.gov/WaterSense/
[13] http://www.energystar.gov/

Although eco-feedback has traditionally *not* been mentioned in legislation oriented around resource efficiency laws, this is beginning to change. Proposals in English legislation, for example, have recently discussed the link between smart meters, occupant behavior, and feedback in reducing electricity demand (Darby, 2008). Depending on the success of eco-feedback systems, one could imagine that consumer-oriented water, electricity and gas eco-feedback be a mandatory part of future building codes just as certain feedback displays are for vehicles (*e.g.,* odometers).

Technological Measures

Technological (hardware) measures, or retrofit programs, have great potential in achieving long-term water savings because they only require a one-time action and require no further effort to maintain water savings (Vickers, 2001). A low-flow toilet (1.6 gallons per flush), for example, installed to replace a traditional 3.5 gpf model could save around 71,000 gallons of water during its average 20 year lifespan (based on the North American average of 5.1 toilet flushes per day per person in the home as listed in Vickers, 2001). Gleick (2006) estimates that by replacing all existing toilets with low-flow versions in California, the state could save 130 billion gallons of water per year. By replacing washing machines with more efficient models, California could save an additional 33 billion gallons a year. This is approximately enough water for the annual needs of 3 million Californians (Glennon, 2009, p 177). Renwick and Archibald (1998) found that installing low flow toilets reduced consumption by 10% per low-flow toilet, low-flow showerheads by 10%, and water efficient irrigation technology by 11%. According to Vickers (2001), since the early 1990s, NYC has saved more than 250 million gallons per day in water and sewer flows through a conservation program that included an aggressive low-volume toilet rebate program involving more than 1 million fixture replacements.

One challenge with technological measures, however, is that they require time, effort and investment on the part of the homeowner—though certainly legislation such as the Energy Policy Act of 1992 accelerates the adoption of such technologies, particularly for new homes. For old homes, Sarac *et al.* (2002) note that public response to retrofit programs are typically positive if (a) the equipment is offered for free and (b) if the program is high-profile and aggressively managed by the water district. However, such retrofit programs may also be rejected on aesthetic grounds or due to lack of knowledge or skill in installing a low-flow fixture. In addition, even if households are interested in adopting low-flow fixtures, external constraints such as the availability or price of the product may prevent them from following through (Jeffrey and Geary, 2006). As such, many water suppliers will offer rebates for low-flow toilets, smart controllers for irrigation, low-flow showerheads and appliances, and pool covers. In some cases, water utilities will give away low-flow fixtures, such as toilets, particularly to multi-family properties such as apartments or condominiums.

Eco-feedback systems for water could analyze water usage patterns and offer personalized recommendations to home occupants about water efficiency upgrades that would require the least effort for the most water savings. In addition, eco-feedback could also be used to identify and locate leaks in the home (*e.g.,* a leaky flapper valve on a toilet). We revisit this potential, in particular, in Chapter 9.

2.4.3.2 Water Pricing

In contrast to the strategies above, water pricing focuses specifically on using market instruments to control demand. Setting the price of water, however, involves issues of monopolies, basic human rights, equity issues, and, as such, is a research area entirely within itself. Here, we only briefly review how water pricing has been used to affect water use.

In general, water rates are designed to meet multiple objectives and must strike a balance between the economic efficiency of a region and the revenue and stability of the water supplier (Hall, 2009). Overall, the cost of water in the US is increasing and will continue to increase as water sources become increasingly scarce. In the 1980s, water rates increased by about 7% per year, which is double the rate of inflation (Jordan, 1999).

With that said, water remains surprisingly cheap given its essential value to humans. In 2002, the average American family spent $474 on water and sewage charges (EPA, 2009), which accounts for about 1.1% of the median household income in the US[14]. Nationwide, Americans pay an average of $2.50 per 1,000 gallons ($0.0025 per gallon) (Glennon, 2009, p224). This is less than all other developed countries except for Canada where water resources are abundant in comparison (Glennon, 2009). Water is actually cheaper than these numbers indicate. In fact, many of us do not actually pay for water itself but rather the costs of delivering the water. That is, the water is free (Glennon, 2009).

Interestingly, eco-feedback would only make these low-rates more visible, which could, paradoxically, serve to encourage *more* use rather than less. However, as water rates continue to

[14] Calculated based on a median household income of $42,409 in 2002, as quoted by U.S. Census Bureau. Retrieved 2009-02-28 from http://www.census.gov/hhes/www/income/histinc/h06AR.html

increase and suppliers increasingly rely on price to control for demand, this point will largely be mitigated. Below, we review the use and effectiveness of pricing water for conservation.

Pricing Water for Conservation

Charging for water on a per unit basis—that is, with payment tied to volumetric use—is generally accepted as one of the most effective methods to encourage conservation (Arlosoroff, 1999). For example, Glennon (2009) reports on the largest study ever undertaken of how water rates affect single-family residential water use in America, which found that water use decreased with water price increases. A consistent point of focus in the literature is the attempt to quantify the price elasticity of water demand—that is, the economic measure of how demand for water shifts in response to price changes (Kenney *et al.*, 2008). Although estimates of price elasticity vary, a review by Brookshire *et al.*, (2002) suggests a typical value of -0.5, which means that a 10% increase in water price leads to a 5% decrease in consumption.

While there are many common rate structures used to charge for water, some rate structures have been developed specifically to target conservation. Inclining block rates (also referred to as inverted block rates or tiered pricing) increase cost with water consumption. Excess use rates, which are an extreme form of *inclining block rates*, trigger an "abusive use" rate that sends a strong price signal to the customer to discourage excessive use (Vickers, 2001). *Seasonal rates*, as the name suggests, vary during different periods of the year and are typically higher in the summer to discourage inefficient *outdoor* use. Finally, *marginal cost pricing* has been a primary topic of research in rate-setting theory and water resource management over the last 25 years (American Water Works Association, 2000). In contrast to average cost-of-service rates, which charge for the treatment, storage, and delivery of water, marginal cost rates incorporate the *added cost* of producing or acquiring new water supply or capacity. These costs are typically higher than the average embedded costs of water and therefore often deter excessive water use.

Despite multiple options for conservation pricing, however, a survey in the year 2000 of water and waste water services of more than 2,200 utilities in the US and Canada found that most utilities used rate structures that are *not* conservation pricing scheme: 36% had a uniform pricing structure, 35% had a declining block structure where water actually gets cheaper with more use, and only 29% had an inclining block structure (Raftelis Environmental Consulting Group, Inc., 2000). There are two main challenges with using price and rate structures to control demand: (1) many individuals lack a clear understanding of their rate structure and water bill raising difficult questions about which price signals customers actually respond to (*e.g.,* see Billings and Agthe, 1980; Shin, 1985; Jordan, 1999) and (2) few customers, if any, receive real-time feedback about their current level of consumption and the current rate charged at that level (if on a block rate scheme). Both of these challenges serve to further motivate the need for more granular water sensing and feedback systems in the home that provide better information on water usage and water cost to the consumer.

One rate structure not mentioned above, which is particularly dependent on providing real-time feedback to customers, is time-of-use pricing. Although seasonal rate structures are a type of time-of-use pricing, the term "time-of-use pricing" is most often used to refer to pricing that changes hourly (or more) to reflect changing supply/demand curves at the utility. Much research exists around the benefits of time-of-use pricing for electricity (*e.g.,* Sexton *et al.*, 1987; Borenstein, 2005; Newsham and Bowker, 2010) but there are no publications, to our knowledge, that study the effect of time-of-use pricing on water usage. The Australian government[15] is currently funding a number of projects investigating time-of-use pricing for water (*e.g.,* Turner, 2010). Although both energy and water have predictable spikes of usage during the day (*e.g.,* peak water usage in residential areas occurs in the early mornings), the problem of peak use for energy has traditionally been more severe because utilities must import additional capacity (often at a much higher cost) or switch on peak capacity generators (*e.g.,* backup coal power plants). More research is necessary to examine time-of-use pricing on water but, as Turner (2010) note, such a pricing scheme is contingent on feedback systems in the home that can inform occupants about current rates.

Water Metering

In order to implement any of the rate structures presented above, water use must be *measured*. Without metering, water suppliers cannot charge based on consumption. In addition to enabling pay-per-use, water metering provides both the consumer and the water utility *with feedback* about consumption. Consumers are able to track their usage over time and potentially identify areas of overuse and utilities can identify leaks and profligate users.

There is much evidence to support the impact that water metering has on driving down consumer water demand; however, because metering is inextricably tied to billing it's not possible to isolate the role of feedback vs. the role of charging for use in effecting demand. In a review of the effect of

[15] Australia is the driest inhabited continent in the world and has experienced a 25% growth rate in the last two decades alone (Gregory and Leo, 2003). As such, the Australian government and water researchers therein have been particularly aggressive in exploring experimental behavior-based techniques in reducing water demand.

household metering on water consumption in Europe and North America, Inman and Jeffrey (2006) found savings between 0-56% (the mean reported savings from US programs was 20%). In the UK, water metering is far less prevalent than in the US—in 1997, only 10% of homes and 80% of businesses were metered. Thames Water, which supplies potable water to Londoners, had 23% of its customer base metered (Thames Water Utilities Limited, 2007). A massive government sponsored four year trial of water meters in the early 1990s found that UK households installed with meters used 11% less water than those without. This difference was particularly marked on peak demand (30% reductions during peak seasons and peak times of day) (Ofwat, 1999; Jeffrey and Geary, 2006).

Although metering is common for single-family households in the US, this is not the case for multi-family dwelling units such as condominiums and apartments. Because individual units are not metered, the building owner pays the water and sewage services directly and a flat fee is incorporated into the rent (or building management fees). Mayer *et al.* (2004b) found that sub-metering (*i.e.,* metering at individual units) led to a 15.6% reduction in per capita demand.

The Complexities of Charging for Water

Given the effectiveness of metering and charging for use, international organizations such as the OECD and the European Union have championed the application of market instruments to efficiently manage demand (Corbella, 2009). The problem, however, is that many people do not think that water should be treated as a pure economic good. In a telephone survey of 2,179 Australian households investigating attitudes to conservation and water consumption, Randolph and Troy (2008) found that although respondents supported differential pricing based on water consumption, a majority (60%) did not think that water prices should be increased to lower water use.

One issue is that higher water bills, which can curb usage, are less affordable to households that have lower incomes. Furthermore, lower-income households may have less ability to reduce consumption because of higher household density, lack of capital to purchase and install water-efficiency devices, and less discretionary use (*e.g.,* lower outdoor consumption) (Beecher *et al.*, 2001). “Some of the highest water users are young families with a large number of children, or people with chronic medical conditions” (Strang, 2004) and, in these cases, there is a converse relationship between levels of use and the ability to pay higher bills. Other concerns involve issues of competing motivations on behalf of the water supplier to raise prices—in other words, the tension between profit and demand management (*e.g.,* see Duke *et al.*, 2002).

In her book, *The Meanings of Water*, Strang (2004) interviews UK residents and water managers about the growing movement to meter households. She quotes a Wessex Water executive who states:

> *Metering is a very emotive issue, and people don't like to think that they are paying for something which is a free resource, which falls out of the sky and just 'miraculously' ends up in their tap through umpteen kilometers of pipe work and treatment plants in a condition which is not harmful to public health.*

Given this reaction, the Water Industry Act of 1999 in the UK prohibits compulsory metering of households except in new homes, in water stressed areas, or during a change in occupancy (Howarth, 2006).

As Michelson *et al.*, 1999 note that although consumers respond to price, the price increases necessary to obtain significant reductions are in debate. In addition, associated increases in revenue are problematic for water suppliers because of regulatory constraints on not-for-profit organizations earning excess revenue.

2.4.4 Water Sensing

Automatic identification of home water usage events has largely been pursued by two non-overlapping efforts: (i) utilities and water resource management scientists and (ii) computing researchers; see Table 2.2 for a summary. Utilities and water resource management scientists have investigated disaggregation to inform government policy (Mayer *et al.*, 2003), plumbing codes (Navigant Consulting, 2010), and to study the effectiveness of conservation programs (Mead and Aravinthan, 2009) and low-flow fixtures (Mayer *et al.*, 2002; Mayer *et al.*, 2003). In contrast, computing researchers have focused on human activity inference (*e.g.,* Fogarty *et al.*, 2006; Tapia *et al.*, 2004) and sustainability applications (*e.g.,* Kim *et al.*, 2008) or both (*e.g.,* Chapters 7 and 8 in this dissertation). We draw upon literature across both fields with a focus on four high-level areas: (1) sensing and inferring human activity in the home, (2) sensing water flow, (3) automatically identifying water usage events, and (4) disaggregating between hot and cold water usage. We address each of these related areas in turn.

Study (year)	Goal	Flow Measurement?	Hot/Cold Disaggregation	Class. Method	Classification Level	Sensing
Ladd and Harrison (1985)	Study residential end uses of hot water	Hot water only, inline	Yes, sub-metered at water heater	Direct sensing	Hot valves only	Inline flow meters (at washer & hot water tank) Elec. current sensors
Weihl and Kempton (1985)	Study residential end uses of hot water	Hot water only, inline	Yes, sub-metered at water heater	Direct sensing	Hot valves only	Inline flow meter (at hot water tank) Temperature sensors
Parliamentary Office of Science and Technology (2000).	Study of residential end uses of water. Lead to SodCon report.	Inline meters at every fixture	Unclear	Direct sensing	Hot and cold valves	Aggregate consumption measured in 3,000 homes plus every appliance/fixture monitored via inline sensors in 100 homes
Lowenstein and Hiller (1996)	Study residential end uses of hot water	Hot water only, inline	Yes, sub-metered at water heater	Flow-trace analysis	Hot valves only	Inline flow meter at hot water tank
Mayer, et. al. (1999)	Study residential end uses of water. Lead to REUWS report.	Yes, inline	No	Flow-trace analysis	Fixture category	Inline flow meter with magnometer to digitize signal
DeOreo and Mayer (2000)	Study residential end uses of hot and cold water	Yes, inline	Yes, sub-metered at water heater	Flow-trace analysis	Fixture category	Dual inline flow meter (whole home meter plus hot water tank meter)
Fogarty, *et al.* (2006)	Activity inference (*e.g.,* for elder care applications)	No	No	Machine learning	Fixture category	Acoustic sensors on intake pipes and drain pipes
Kim, *et al.* (2008)	Eco-feedback	Yes, inline	Yes, direct	Direct sensing	Untested (lab study only)	Inline meter accelerometers on pipe
Chapter 7	Activity Inference / Eco-feedback	Yes, calibrated from pressure	Yes	Machine learning	Valve	Single pressure sensor
Chapter 8	Activity Inference / Eco-feedback	Yes, calibrated from pressure	Yes	Machine learning	Valve	Tested single pressure sensor, dual pressure sensor and used custom ground truth collection system for evaluation
Chen *et al.* (2011)	Eco-feedback	Yes, 15 min resolution	No	Machine learning	Fixture category	Inline smart meter (15 min interval data)

Table 2.2: A history of residential water sensing for disaggregation purposes sorted by year.

2.4.4.1 Sensing Human Activity in the Home

Prior work has demonstrated at least three approaches to the fundamental challenge of sensing human activity in the physical world: mobile and wearable sensing, distributed direct environmental sensing, and infrastructure-mediated environmental sensing. Promising mobile and wearable activity sensing methods include accelerometer-based activity recognition (Bao and Intille, 2004, Lester, *et al.*, 2005) and the detection of interaction with tagged objects via a wearable RFID reader (Philipose *et al.*, 2004). There are many compelling applications of mobile and wearable methods, but they share a common need for a person to be willing to wear or carry the necessary device.

Environmental sensing systems take a complementary perspective, instrumenting an environment to detect activity within it. In the home, distributed direct sensing can be based on computer vision (Brunnitt *et al.*, 2000), microphones within the living environment (Chen *et al.*, 2005), many simple sensors throughout the home (*e.g.,* reed switches on cabinet doors, accelerometer-based object manipulation sensors, infrared motion and break-beam sensors: Tapia *et al.*, 2004; Tapia *et al.*, 2006; Wilson and Atkeson, 2005), or a smaller number of targeted direct sensors (*e.g.,* strain sensors under floorboards at strategic locations, Rowan and Mynatt, 2005). Direct sensing provides valuable insight into home activities, but comes with practical costs. Installation and maintenance can be cost-prohibitive, direct sensing can create privacy concerns and a feeling of stigmatization (especially with cameras or microphones), and a littering of sensors throughout a home can be problematic with children and pets (Beckmann *et al.,* 2005; Hirsch *et al.*, 2000).

Infrastructure-mediated sensing has therefore evolved to help address many practical obstacles to everyday deployment of home activity sensing, but is inherently limited by what information can be practically and reliably extracted from a home's infrastructure. The limitations of existing approaches are especially salient for water. Fogarty *et al.* used microphones pressed against the exterior of a home's major water pipes (cold water inlet, hot water inlet, waste water exit) to demonstrate recognition based on temporal patterns of water use (*e.g.,* the series of fill cycles associated with a dishwasher, Fogarty *et al.*, 2006). However, Fogarty *et al.* (2006) found they could not reliably differentiate among multiple instances of similar fixtures (*e.g.,* multiple sinks or toilets within a home), could not reliably identify concurrent activities (*e.g.,* a toilet flush while a person is showering), and did not attempt to estimate the volume of water being used. They also reported difficulties with ambient noise and audio-based sensors (*e.g.,* an air conditioning unit in close proximity to a sensor placed on a home's hot water heater). By addressing these shortcomings, HydroSense significantly advances the state-of-the-art for water-mediated home activity sensing.

2.4.4.2 Sensing Water Flow

There are two basic approaches for measuring water flow: *inline direct* flow measurement and *non-intrusive flow* estimation. Inline systems typically use either positive displacement or velocity measurements to calculate flow. Positive displacement relies on water to physically displace the measuring element (*e.g.,* an oscillating piston or rotating disc) in proportion to water flow volume. Most residential meters use positive displacement because it is generally accurate at the low to moderate flow rates found in the residential sector (Satterfield and Bhardwai, 2004).

Meters that do not require physical contact with water flow are called *non-intrusive*. These methods are attractive because they do not require pipe modification for installation, which can be costly and requires the expertise of a plumber. Non-intrusive flow estimation techniques use either active or passive sensing approaches. Many active sensing systems use a non-intrusive actuation probe that is distorted by water flow and perceived by an associated sensor. For example, Ultrasonic Doppler Velocimetry (UDV) uses the sound transit time and Doppler shift from pulsating ultrasonic waves emitted into the fluid flow to determine velocity (Takeda, 1995). Similar methods have been developed using lasers (*e.g.,* Laser Doppler Velocimetry, Foreman *et al.*, 1965). A more recent technique, called Particle Image Velocimetry, uses computer vision to record the position of tracer particles injected into the stream over time (Adrian, 2004). Although each of these techniques are often extremely accurate and can be used to measure flow of dangerous liquids (*e.g.,* hot metallic melts), they are intended for industrial applications (*e.g.,* manufacturing plants or large-scale irrigation systems) and thus are prohibitively expensive for typical residential users (with units ranging in price from $2,000–8,000).

Lower-cost non-intrusive techniques have been proposed and investigated that use *passive* sensing. Evans *et al.* showed in a laboratory environment that accelerometers mounted on the exterior of water pipes have a strong deterministic relationship to water flow rate (Evans *et al.*, 2004), but this is highly sensitive to pipe diameter, material, and configuration. Kim *et al.* demonstrated the use of an aggregate water flow meter together with a network of accelerometers on pipes to infer flow rates throughout a home (Kim *et al.*, 2008). Both of these approaches require placement of multiple sensors along water pipe pathways that are uniquely associated with each fixture of interest (*i.e.,* they are distributed direct sensing methods).

The next generation of resource measurement systems (often referred to as "smart meters") will soon provide real-time (or near real-time) data on electricity, gas, and water usage in homes and businesses. It is unclear, however, if this data will be open or closed (*i.e.,* proprietary) and what temporal resolution will be available (most smart meters advertise fifteen minute interval data). For those water meters not yet upgraded to their smart meter counterparts, a popular and low-cost non-intrusive retrofit has emerged using magnetic sensors. Most residential meters use magnetic coupling to transfer data between the rotating disc, which spins proportional to flow rate, and the counter unit, which converts this spin rate to flow. Magnetic sensors, such as a hall effect sensor, can be placed at the top or bottom of a residential water meter to sense this spinning magnetic field and convert the spin rate to flow (*e.g.,* Cheung, 2009; Mayer *et al.*, 1999). AquaCraft[16] has used this

[16] Aquacraft Corporation: http://www.aquacraft.com. While AquaCraft uses the Meter-Master Model 100EL flow recorder by the F.S. Brainard Company to record flow traces on meters, much cheaper solutions are available. DIY'ers such as Ed Cheung have created Hall effect based flow trace units for sub $100 (Cheung, 2009).

approach since 1996 to digitize traditional inline water meters and perform flow-trace analysis, a technique used to automatically identify water usage events.

2.4.4.3 Identifying Water Usage Events

The goal of automatically identifying water usage events in the home has been pursued by utilities and water resource management scientists to better understand residential end uses of water. Only recently, with advances in technology and reductions in cost, has the ability to measure water at a disaggregated level from a *single installation* point been possible. In 1992, Dziegielewski, *et al.* (1992) proposed what is now the standard water usage event identification technique in the water research industry called *flow-trace analysis*. Flow-trace analysis works by analyzing the aggregate flow trace patterns off of an inline water meter to determine the source of the water usage event. Flow-trace analysis relies on the fact that most residential water uses exhibit highly consistent behavior over time (*i.e.,* a specific toilet will flush with the same volume and flow; similarly a specific dishwasher will exhibit the same series of flow patterns each time it is run, Mayer *et al.*, 1999).

Flow-trace analysis has since been used in a number of government- and utility- sponsored studies of residential end uses of water (DeOreo *et al.*, 1994; DeOreo *et al.*, 1996a; Lowenstein and Hiller, 1996; Mayer, 1995; see also Table 2.2). The most popular of which is a study conducted by the American Water Works Association Research Foundation (AWWARF), which used AquaCraft's flow-trace analysis toolkit called *Trace Wizard* to study residential end uses of water in 1,188 households across 12 study sites in America and Canada (Mayer *et al.*, 1999). The water data was collected using the aforementioned magnetic sensing retrofit solution. The data collection took place in the winter and the summer months from 1996 to 1998 and resulted in 1.9 million water usage events. A total of four weeks of water data per home was collected in separate two-week intervals. This study provided the canonical dataset upon which most US government statistics of residential end uses of water are based (Vickers, 2001). That said, as far as we are aware, the accuracy of flow-trace analysis has not been comprehensively studied. In the AWWARF study, the authors speculate that their system is 90 percent accurate in correctly identifying water usage events (p47 in Mayer *et al.*, 1999); however, they were not able to offer concrete accuracy statistics as they did not collect ground truth data.

In the only known empirical investigation, Wilkes *et al.* conducted staged experiments of water usage over a five day period in one home. Flow-trace analysis correctly categorized 83% of the *isolated* water usage events at the fixture category level. When water usage overlapped (*i.e.,* what we term *compound events*), performance dropped dramatically to 24% when two water fixtures were used in compound and 0% when three or more were used (Wilkes *et al.*, 2005). Moreover, it is important to note that although flow-trace analysis is capable of classifying at the fixture category level, it cannot be used to determine the specific fixture or valve that was used (*i.e.,* it can sense that *a* toilet was flushed, but not *which* toilet was flushed). In contrast, HydroSense can identify water usage events at the valve level.

Finally, in its current form, flow-trace analysis is not completely automated. Usage of AquaCraft's Trace Wizard, for example, is a multi-step, iterative process. The program uses the following set of statistics to help classify water usage events: start time, stop time, duration, volume (gallons[17]), peak flow rate in gallons per minute (gpm[18]), the most common flow rate (gpm), and how often this most common flow rate occurs during the duration of the event. Events are classified according to their similarity with a pre-defined set of manually entered and tuned per-home parameters. For example, a toilet may be defined as using between 3.25 and 3.75 gallons per flush, the peak re-fill flow rate as between 4.2 and 4.6 gpm, the duration of the flush event between 30 and 50 seconds, and the mode flow rate between 4 and 4.5 gpm (Mayer *et al.*, 1999). AquaCraft estimates that it takes their trained analysts approximately one hour per week of data from a home to complete a flow trace analysis; less time after the parameter file has been properly tuned (Mayer *et al.*, 1999).

2.4.4.4 Disambiguating Hot Water vs. Cold Water Usage

The lack of precise measurements about the quantities of hot water used in residences has been an obstacle in the design of hot water systems (*e.g.,* measuring how much hot water homes require at peak use: DeOreo *et al.*, 2000; Hiller, 1998) and in the analysis of conservation programs (*e.g.,* measuring hot water savings from a low-flow shower head: Dziegielewski, 1992). Hot water usage also highlights the strong interconnection between energy and water conservation efforts in the home. According to the US Department of Energy, hot water heating is the fourth most energy consuming activity in the home behind air conditioning, refrigeration, and space heating (U.S. Department of Energy, 2001); however, *what* hot water usage activities contribute to this consumption are much less understood (Henze *et al.*, 2002).

The measurement and analysis of domestic hot water consumption is typically accomplished using one of two methods: a temperature-based inference method or a flow-trace analysis method

[17] 1 US gallon ≈ 3.785 L
[18] 1 gpm ≈ 0.063 liters / sec

(where the inline meters are installed at the hot water heater intake line: Aguilar *et al.*, 2005). In 1985, Weihl and Kempton conducted the first quantitative study of hot water usage using automatic means (Weihl and Kempton, 1985). They installed an inline flow meter and a temperature probe at the hot water tank as well as temperature probes at the hot water pipes leading to each fixture. Flow rate and temperature were recorded to a computerized data logger once per minute. From this data, the authors were able to deduce which fixtures were using water, how much hot water was being used, and also calculate pipe heat loss. Ladd and Harrison used a similar distributed sensing approach; instead of temperature probes, however, they used power consumption monitors on the dishwasher and clothes washer, an inline flow meter installed at the clothes washer, and an inline flow meter at the hot water tank (Ladd and Harrison, 1985).

Lowenstein and Hiller (1996) simplified the above approaches by eliminating the need for multiple sensors. They collected flow trace data at 15 second intervals at an inline meter installed at the hot water tank feed line. The volume of flow and the average flow rate for each hot water draw were used to classify the hot water usage events into their end use-category, a technique they referred to as "bin analysis," but is simply a reduced form of flow-trace analysis with fewer parameters (*e.g.,* without time of day, event duration). Although this technique was used successfully in a year-long study of seventeen sites (and repeated by DeOreo and Mayer (2000) in a study of 14 Seattle homes), it was noted by the authors in a follow-up paper (Lowenstein *et al.*, 1998) to have two major limitations: (1) they were not able to discriminate between end uses when multiple hot water activities occurred at the same time and (2) hot water draws for different end-uses can have the same flow rate and total flow volume, making it difficult to unambiguously associate specific end-uses. Thus, in their follow-up study, they attached thermocouples 1-3 inches[19] downstream from where the hot water line branched, up to three thermocouples per home (depending on its plumbing layout) to mitigate these limitations.

The water sensing system in this dissertation, HydroSense (Chapters 7 and 8), presents a unique opportunity for discriminating between hot and cold water usage because it is much easier to install than the above approaches. Pressure waves are shaped not just by the valve type but also by their propagation pathway through the pipe system, allowing HydroSense to disambiguate hot water events from cold water events (even though the hot and cold water valves are right next to each other at a faucet, their pipe pathway through the home is quite different).

[19] 1 inch ≈ 2.54 cm

2.4.4.5 Summary of Water Sensing

Although past research has explored disaggregation approaches using only one or a few sensors, no work exists on automatically identifying water usage down to the individual fixture or valve. Similarly, although a number of researchers have explored sensing techniques for hot water consumption in the home, no current method exists for disambiguating hot vs. cold water use from a single sensor. In this dissertation (Chapters 7 and 8 specifically), we explore the use of pressure-based sensing to do both.

2.4.5 Water Feedback

Similar to the water sensing research above, the water feedback work has largely been pursued by three fairly disparate communities: (i) utilities and water resource management scientists; (ii) HCI/Ubicomp researchers; (iii) environmental psychologists. In this section, we review the water feedback literature with a focus on both the *design* and the *evaluation* of the water feedback system. We note that our literature search was unable to find any past or current work that focuses on *disaggregated* water usage data, which is the focus of Chapter 9. Thus, the related work presented below is exclusively focused on either point-of-consumption water sensing and feedback systems (*e.g.,* Kuznetsov and Paulos, 2010) or systems that present aggregate water usage information (*e.g.,* Naphade, 2011).

2.4.5.1 The Design of Eco-Feedback Systems for Water

In terms of the water feedback designs, we can use the eco-feedback design space presented in Chapter 4 to help structure our discussion. The more primitive design dimensions include: *data granularity*, *update frequency, display medium*, and the *location of feedback*. These are tightly bound together, particularly for the HCI water feedback systems because most are *point-of-consumption* sensing and feedback systems—in other words, they measure water usage directly at the faucet (or showerhead) and provide immediate feedback about that usage via an ambient display. This is likely a reflection of the difficulty in building eco-feedback systems for water where the sensor is independent (physically disjoint) from the feedback system. This limitation should be alleviated in some fashion by the recent introduction and proliferation of water-based smart meters (although these are still far less common than for electricity). Even still, as previously mentioned, these systems only provide aggregate consumption information at intervals less frequently than real-time. In addition, it is unclear if smart meter data will even be open and accessible to researchers or hobbyists to build their own feedback systems.

Kuznetsov and Paulos (2010), for example, created *UpStream*, a custom-designed orb display that lights up in green, orange, and red colors depending on the length of time a faucet or shower is used; an LED graph accompanies this display to relate total usage at that fixture so far for the day (Figure 2.4j and k). Similarly, the *show-me* display by Kappel and Grechenig (2009) uses a string of LED lights, which illuminate in a progress-bar like fashion as water flows from a showerhead (Figure 2.4i). The design community has also predominantly explored *point-of-consumption* feedback (Figure 2.4a through f), even though their prototype sketches are not bound by the same pragmatic constraints as the HCI researchers who typically implement and evaluate their systems. It is unclear, in these cases, why point-of-consumption feedback has received so much attention.

Although point-of-consumption feedback can potentially reduce usage at the installed fixture (Willis *et al.*, 2010; Staake *et al.,* 2011), it is limited in its ability to convey broader patterns of use or to easily compare usage across fixtures. These systems have also disproportionately focused on faucet and shower usage, which account for only 22% of water use in the average North American home (Vickers, 2001). Also, because these systems require installation at each fixture (*i.e.,* they use a direct sensing approach), there are pragmatic issues around adoption that are rarely addressed such as increased maintenance, power requirements at each water outlet, and a change in the aesthetic of the fixture. This latter point is already an issue affecting the adoption of low-flow fixtures (Jeffrey and Geary, 2006). In contrast, our displays are designed for sensing systems that need not be collocated with a fixture and can therefore support a wider range of visualizations (*e.g.,* comparison of all fixtures usages within one display).

Figure 2.4: Thus far, most water-based eco-feedback systems have been designed to sense and feedback water usage at the *point-of-consumption*. The top two rows are design sketches/conceptions created by industrial designers while the bottom two rows are actual systems built and evaluated by HCI researchers. Starting from the top-left: (a) *Squirt* by Meghana Vaidyanathan (Lockton, 2007) is aimed at children aged 3 to 6. (b) *In-Formed* by Nadeen Haidary redirects a small portion of water to a glass chamber, which acts as a bar graph tracking current usage. (c) *Insight/Inmind* by Adam Kereliuk (Morell, 2007) uses a backlit LCD display to show how much water usage a faucet/shower has used by day, week or month; the next three designs are similar: (d) *TapMeter* by Henry Ellis-Paul, (e) *Domestic Water Meter* by Viktor Legin, (f) *iSave* by Yu Guogun (Morell, 2007). (g) *HeatSink* (Arroyo *et al.*, 2005) illuminates water according to temperature while (h) *WaterBot* (Arroyo *et al.*, 2005) offers continuous feedback via visual and auditory cues. (i) The *Show-Me* shower display by Kappel and Grechenig (2009) illuminates a string of LEDs according to usage. (j) and (k) show various *UpStream* prototypes for faucets and showers by Kuznetsov and Paulos (2010). (l) The *Shower Calendar* by Laschke *et al.*(2011) uses a projected display on a shower curtain to show shower usage amounts over time (colors represent people; larger dots mean *less* water usage during that shower).

2.4.5.2 Evaluating Water-Based Eco-Feedback Systems

The environmental psychologists and water resource management scientists have largely focused on large-scale studies with simple feedback technology—in some cases handwritten notecards—to study how and in what ways feedback on water usage may change behavior (*e.g.,* Geller *et al.*, 1983; Aitken *et al.*, 1994; Willis *et al.*, 2010). In contrast, the HCI community has focused on creating novel water feedback prototypes and evaluating these via informal user studies. In this case, the visualization system—its understandability, its interactivity, its aesthetic—is typically the focus of the research rather than the effect of the system on behavior. Although a few HCI studies do attempt to deploy and run intervention-based studies of their technology (*e.g.,* Kappel and Grechenig, 2009; Kuznetsov, 2010; Laschke *et al.*, 2011); these are small-scale and not always methodologically rigorous. Indeed, they are often meant to point to the potential of the feedback system rather than to prove or scientifically demonstrate its effectiveness. This methodological difference between the two disciplines is explored further in Chapter 3.

A review of the various water feedback artifacts and their evaluations is presented in Table 2.3. Four of the studies reviewed provide feedback on aggregate water consumption, which refers to the *total* water usage in a building rather than at the point-of-consumption for a particular fixture or appliance (as previously noted no studies exist investigating the effect of disaggregated water usage data on consumption behaviors). In the two environmental psychology studies (Geller *et al.*, 1983 and Aitken *et al.*, 1994), hand-delivered notecards provided feedback on the previous day's (Geller *et al.*, 1983) or week's (Aitken *et al.*, 1994) water usage to households. The Aitken *et al.* study ran for nine weeks with a three-week baseline data collection period, a three-week intervention period, and a three-week post-intervention period. The researchers found that the high-consuming households receiving feedback plus a cognitive dissonance treatment significantly reduced their water consumption. In the Geller *et al.* study, feedback was not found to affect consumption. The authors argue that the limited effectiveness of feedback "was most likely a function of resource cost (*i.e.,* water prices) and the lack of economic incentives for reducing consumption." They argue further that "in previous energy research, feedback strategies implemented in areas where electricity was relatively inexpensive had much less of an impact than did feedback interventions applied in areas where electricity was expensive (Geller *et al.*, 1982; Winkler & Winett, 1982)." Winkler (1982) reported that where water prices are low behavioral interventions can be expected to have minimal or no influence.

Authors	Publication Venue	Year	Feedback Description	Motivation Technique(s)	Feedback Granularity	Feedbackf Freq.	Implemented	Feedback Study	Feedback Results
Geller *et al.*	Journal of Population and Environment	1983	Hand-delivered postcards were delivered to the feedback residences with yesterday's consumption amount in gallons, % increase / decrease from previous postcard, and % increase / decrease from baseline. Smiley/frowning faces were provided for each of the percentages included.	Feedback, Comparison, Rewards, Penalties	Aggregate (building level)	Daily	Yes	Total households N=129; Feedback intervention group N=66; Four weeks of baseline data collection; intervention period lasted for five weeks.	Feedback group resulted in no significant reductions over baseline group.
Aitken *et al.*	Journal of Applied Social Psychology	1994	Hand-delivered postcards with a commitment statement, feedback amount from past week, and comparison with households of same size made artificially low to "increase potential to be influenced by treatment."	Feedback, Commitment, Social Comparison	Aggregate (building level)	Weekly	Yes	Total households N=226; 3-study conditions; Feedback Intervention group N=107; Baseline=3 weeks; Intervention=3 weeks; post-intervention period=3 weeks	Feedback only group did not result in significant reductions over control. Feedback+cognitive dissonance group resulted in 4.3% reduction in use across highest consumers.
Arroyo *et al.*	CHI	2005	Waterbot is a point of consumption sensor and feedback display for water consumption. Two LED bars represent current use and average household use. "Positive" auditory cues are used every time tap is closed to "act as positive reinforcers for turning off water."	Feedback, Rewards, Social Comparison	Point-of-consumption at faucet	Real-time	Yes, prototype	Two informal pilot studies (N=10, N=15)conducted in laboratory focused on understandability and aesthetics of system.	Not a behavioral study. Qualitative findings include: bar graphs, temperature feedback, and "just-in time" messages were intuitively understood.
Petersen *et al.*	Journal of Sustainability in Higher Education	2007	Website (and some kiosks) accessible by students on campus provided dorm-level feedback of electricity and water consumption	Feedback, Social-Comparison, Competition	Aggregate (building level)	Real-time	Yes, now commercial product via Lucid Design.	Two dormitories; 3-week baseline period; 2-week competition period; 2-week post-competition period	32% reduction in electricity usage and a 3% reduction in water usage.
Kappel & Grechenig	Persuasive	2009	Water shower monitor and ambient feedback display that uses a vertical row of LEDs that light up in proportion to the amount of water used (like a bar graph).	Feedback	Point-of-consumption at shower	Real-time	Yes, prototype	Pilot study: N=4 households; no baseline data; intervention period=3 weeks	Paper says "mean water consumption decreased by 10 liters." Unclear if this is overall or per-shower. Also, no control group or baseline data so unclear how this number was calculated.
Ravandi, *et al.*	HCI International	2009	Display system for shower using fishtank and game design elements. Users login when they shower.	Feedback, Self- & Social-Comparison Penalties, Rewards	Point-of-consumption at shower	Real-time	No, design only	None	No evaluation.
Kuznetsov & Paulos	CHI	2010	Low-cost point of consumption displays for faucets and showers. Two styles of displays were created for showers: (i) a numeric display with current and aver usage and (ii) an ambient visualization orb, which would grow green, orange, & red depending on shower length.	Feedback, Penalties, Comparison	Point-of-consumption at shower and faucet	Real-time	Yes, prototype	3 pilot studies; one of faucet display and two of shower; 1st /2nd study: 1-3 days; 3rd study: 4-7 days	Mixed results. Public faucet display resulted in increased usage (perhaps because of novelty effects: participants were driven to use water more to see how display would change). Private displays reduced usage. Study durations prob. too short to generalize results.
Laschke, *et al.*	CHI Extended Abstracts	2011	Shower design prototype that displays water usage for individual users (users login when they take a shower).	Feedback, Self- & Social-Comparison,	Point-of-consumption at shower	Real-time	Yes, prototype	Pilot study: 2 households for 1 month	Mixed results. Study primarily focused on qualitative reactions. Very small study; again difficult to generalize quantitative results.
Willis *et al.*	Journal of Resources, Conservation, & Recycling	2010	Used Waitek shower monitors, which provide real-time usage on showering. Plays auditory alert when shower time passes 5 min threshold.	Feedback, Penalties, Comparison	Point-of-consumption at shower	Real-time	Yes, commercial product	Total households N=151; Feedback intervention N=44; 2 week baseline winter 2008; 2 week intervention winter 2009.	27% reduction in mean shower event volumes in feedback group compared to control.
Naphade *et al.*	IBM Tech Report	2011	Online web portal showing aggregate water usage over time and weekly printed reports. Households could also receive leak alerts, compare their usage to others, and participate in competitions/contests.	Feedback, Self- & Social-Comparison, Rewards, Competition, Alerts	Aggregate (building level)	"Near real-time"	Yes, pilot commercial product	Total households N=303; Feedback intervention N=151; Control=152; 9-week	Average overall water savings of 6.6% per household. In addition, 8% reported leaks compared to 0.98% across rest of city. Active participation rate of 44%.
Staake *et al.*	ETH Zurich Tech Report	2011	Point-of-consumption feedback system for shower. Report is sparse on design details.	Feedback, other strategies unclear	Point-of-consumption	Real-time	Yes, pilot comm. Product	200 households sent device; 91 installed device. 5 mo. Study period w/ baseline collection.	Average shower water consumption reduced 22.2% (compared to first 9 showers after device installed but no feedback given).

Table 2.3: A review of water feedback displays in the HCI, environmental psychology, and water resource management literature sorted by year.

In a more recent study conducted by IBM Research, Naphade *et al.* (2011) designed and implemented a pilot feedback program using smart water meters in Dubuque, IA. Their study involved a 9-week behavioral study of 303 households (151 in experimental group, 152 in control group) studying effects of an online web portal (Figure 2.5) and printed weekly reports of water usage data. These interventions not only presented water usage patterns and trends but also automatically detected and reported leaks. They found an average overall savings of 6.6% per household compared to control group. In addition, pilot participants reported leaks at a rate of 8% compared to 0.98% city-wide (the authors estimate that 30% of households in the city had leaks). These findings point to the potential of new, emerging sensing and feedback systems in reducing water usage consumption.

Finally, although not just about feedback, the effect of metering on water usage behavior is also relevant. Metering's primary purpose is to allow water suppliers to charge based on usage. As a consequence, monthly or bi-monthly bills are provided to consumers with information on their aggregate water consumption for the billing period (these are also available online with increased frequency). Because metering is inextricably tied to billing, its effect on behavior is as much about economics and perceptions of cost as it is about feedback. In a review of the effect of household metering on water consumption in Europe and North America, Inman and Jeffrey (2006) found savings between 0-56% (the mean reported savings from US programs was 20%). As previously noted, however, charging for water via household metering is a contentious and emotive issue involving debates around water equity and water as a social good vs. a commodity. Thus, other strategies for feedback may deserve increased attention.

2.4.5.3 Summary of Water Feedback

A large portion of the water feedback related work has focused on point-of-consumption feedback. Although recently, this type of feedback has been evaluated in large behavioral studies and shown to be effective (*e.g.,* Willis *et al.*, 2010; Staake *et al.,* 2011), these systems have also disproportionately focused on faucet and shower usage, which account for only a small portion of water use in the average North American home (Vickers, 2001). Inspired by our formative work in Chapter 6 and our sensing work in Chapters 7 and 8, we explore a range of eco-feedback designs of *disaggregated* usage data, which have not been evaluated before.

Figure 2.5: Three commercial eco-feedback systems for water: (a) The *Shower Monitor* by Waitek starts with a full "progress-bar" that decreases according to sensed flow rate and water temperature. After a preset amount of water has been used, a beeper alarm sounds (see Willis *et al.*, 2010). (b) The start-up company *Amphiro* has recently pilot tested their miniaturized smart meters with wirelessly connected displays; however, little information exists on the design of their system (see Staake *et al.*, 2011). (c) The IBM Smarter City Water Pilot (Naphade *et al.*, 2011) is an online website for smart meter water data that was deployed to 151 households over a 9-week period. These three designs were also evaluated in behavioral studies, see Table 2.3.

2.5 CHAPTER SUMMARY

In this chapter, we first traced the short history of Sustainable HCI research and positioned eco-feedback research within the broader HCI/Ubicomp research communities. We also connected eco-feedback research to the HCI and computer graphics sub-discipline of information visualization. In particular, we noted how eco-feedback could be seen as a relatively new, emerging area of infovis called Casual Information Visualization. This link is useful because it provides an existing vocabulary with which to think about, discuss and critique eco-feedback designs as well as to draw upon infovis findings in the design of eco-feedback systems.

We then transitioned to literature on sensing and feedback for personal transportation and water usage. Here, we noted that new mobile phone models released since our UbiGreen tool was developed (Chapter 5) may eliminate the need for a wearable sensor for activity inference. Perhaps more interestingly, however, we found that although new transit transportation mode inference techniques have emerged since our UbiGreen work was conducted, no new eco-feedback applications have been published that take advantage of those systems.

For work related to eco-feedback for water usage, we first provided background on water usage in general to better contextualize our contributions. We included a short description of the hydrologic cycle, argued for the importance of conservation-related research around residential water usage, and reviewed water management programs and strategies, delineating non-pricing and pricing techniques to curb water use. Finally, we reviewed work related to sensing and feedback systems for water, including disaggregation methods, water flow sensing techniques, and hot vs. cold disambiguation. The water feedback literature demonstrated the promise of eco-feedback in reducing water usage as well as open opportunities. Namely, no past work has presented an automated sensing system for disaggregating water usage at the individual fixture level nor does any past work exist on how such granularities of data may be visualized to the user.

Review and synthesis of related work continues in the next two chapters. Chapter 3 compares eco-feedback work in HCI/Ubicomp to that in other disciplines, while Chapter 4 presents motivational theories and techniques useful for eco-feedback research, as well as a design space that incorporates much of the discussion in Chapters 2 and 3.

Chapter 3
Investigating the Role of HCI in the Design and Evaluation of Eco-Feedback Technology

Given the rapid rise of eco-feedback related research in HCI, as highlighted by Section 2.1 in the previous chapter, it is critical for the HCI community to reflect upon and define an approach and theoretical foundation for the design and evaluation of eco-feedback technology. This chapter and the next (Chapter 4) contribute specifically to this area of eco-feedback research.

While the stated goal of eco-feedback technology is to provide feedback on individual or group behaviors to reduce environmental impact (adapted from: McCalley and Midden, 1998; Holmes, 2007), few HCI eco-feedback studies have even attempted to measure behavior change. Although eco-feedback may be seen as an extension of research in persuasive technology (Fogg, 2002), studies of eco-feedback actually extend back more than 40 years in fields such as environmental psychology and applied social psychology. This gives rise to two interrelated questions: (1) What can HCI learn from environmental psychology and (2) what should be the role of the HCI community in contributing to eco-feedback research?

Although some researchers in HCI and Ubicomp have applied findings from environmental psychology (*e.g.,* Pierce *et al.*, 2008 and Woodruff *et al.*, 2008), all too often these findings have been ignored. As far back as the 1970s, studies have shown that eco-feedback technology can affect consumption behaviors. For example, in 1974 Kohlenberg *et al.* found that a light bulb, which illuminated when households were within 90% of their peak energy levels, changed energy usage behaviors (study published in Kohlenberg *et al.*, 1976). At that time, environmental psychology was an emerging discipline that had grown out of the realization that environmental conservation was a twofold problem: partly technical and partly human.

The gap between eco-feedback research in HCI and in environmental psychology is unfortunate because it can lead to redundant efforts and, at worst, ineffective designs. This oversight not only affects researchers of eco-feedback technology but also practitioners, as commercial eco-feedback systems become more widely deployed and governments begin instituting the use of home resource feedback systems (*e.g.,* see Darby, 2008).

In this chapter, we bridge the gap between findings from environmental psychology and the design and evaluation of eco-feedback systems in HCI. We conduct a comparative survey of 44 papers studying eco-feedback technology in the HCI/Ubicomp literature and 12 papers within the environmental psychology literature. We use this survey to contrast the design and evaluation approaches taken in these disciplines and to identify areas in which HCI can make the strongest contribution. Finally, we close with a discussion of issues that warrant further attention in the HCI community including approaches to evaluation and the lifecycle of usefulness of eco-feedback systems. The next chapter (Chapter 4) provides a complementary perspective and shifts from comparing eco-feedback designs and evaluation methodologies between the two fields to integrating findings from environmental psychology (and other disciplines) into eco-feedback designs. We begin this chapter with a review of eco-feedback studies in environmental psychology.

3.1 REVIEW OF ECO-FEEDBACK STUDIES IN ENVIRONMENTAL PSYCHOLOGY

Research on the effects of feedback on consumption behaviors spans four decades and two important eras: the energy crisis of the 1970s and 80s and the climate change era beginning in 1995 (Ehrhardt-Martinez *et al.*, 2010). Most of this research has focused on the effect of energy feedback on either electricity or natural gas consumption behaviors rather than the two topics explored in this dissertation: transportation and water. The major literature reviews of eco-feedback studies are by Katzev, 1987; Darby, 2000; Abrahamse *et al.* 2005; Fischer, 2008; EPRI, 2009; and Ehrhardt-Martinez *et al.*, 2010. The research reviewed in these papers is conducted by applied or environmental psychologists, governments or utility companies, and only two of the papers (EPRI, 2009; Ehrhardt-Martinez *et al.*, 2010) cite HCI literature: Chetty *et al.*'s (2008) fieldwork of understanding resource consumption in the home published at UbiComp 2008.This is both a reflection of disciplinary boundaries and the recency with which HCI has engaged with eco-feedback research but also, perhaps, the ways in which these other fields perceive the relevancy of HCI work.

Abrahamse *et al.* (2005) provided the first review of intervention studies aimed at reducing household energy consumption of the modern era. The authors investigated thirty-eight studies performed within the field of social and environmental psychology and categorized their results using Katzev and Johnson's (1987) taxonomy of techniques for promoting energy conservation (see Chapter 4 for a detailed discussion): antecedent strategies (*i.e.,* commitment, goal setting, information) or consequence strategies (*i.e.,* feedback, rewards, penalties). Abrahamse *et al.* (2005) specifically explored: (1) to what extent did the intervention result in behavioral changes and/or reductions in energy usage; (2) what were the underlying behavioral determinants examined (*e.g.,* knowledge, attitudes); (3) to what extent could effects be attributed to the interventions; (4) and were the effects maintained over long periods of time. The authors found that most studies focused on voluntary behavior change with methods that involved changing an individual's knowledge and/or perceptions rather than by changing their surrounding contextual factors (*i.e.,* pay rate structures for energy). In terms of the interventions themselves, Abrahamse *et al.* found that reward-based and feedback interventions effectively encouraged energy conservation (with varying degrees of success). Important findings include that information alone was sufficient in increasing knowledge levels but not necessarily in inducing behavior change (or energy savings). Results of studies using feedback suggest that increasing the frequency of feedback and combining feedback with goal setting were most successful; no conclusive results were found when comparing feedback in terms of monetary rather than environmental costs or in providing comparative feedback (*e.g.,* comparing to social groups).

Fischer (2008) reviewed approximately twenty studies and five compilation publications from 1987 onward exploring the effects of feedback on electricity consumption and on consumer reactions, attitudes, and wishes concerning such feedback. She found that typical energy savings were between 5 and 12% (though the absolute range was between 0 – 20%). In a similar review of thirty-eight feedback studies carried out over a period of 25 years, Darby (2006), found typical energy savings of 10-15%. Darby introduces a distinction between *direct* and *indirect* feedback; direct provides immediate information on an activity in real-time while indirect provides feedback sometime after the consumption occurs (*e.g.,* like utility bills). Both Fischer and Darby point out the difficulty in synthesizing, comparing, and categorizing these studies as they range in sample size (from 3 to 2,000), housing type, and feedback method (*e.g.,* frequency of update, historical duration, visual design). Also, in some studies, other interventions such as financial incentives and goal-setting were used in addition to feedback, making direct comparisons across studies difficult. Despite such disclaimers, as Fischer argues, the sheer number of studies that reported savings is a good indicator for the general effectiveness of using feedback to change consumption behaviors.

In 2009, the Electric Power Research Institute (EPRI, 2009) released a comprehensive follow-up to the above literature reviews with a specific focus on synthesizing feedback results, comparing two theoretical perspectives on how consumers make consumption decisions and the role of information in informing these decisions, and highlighting outstanding research questions. The EPRI report expanded Darby's notion of indirect and direct feedback into six sub-categories; the first four are indirect: (1) standard billing, (2) enhanced billing, (3) estimated feedback, and (4) daily/weekly feedback while the other two are direct: (5) real-time feedback and (6) real-time plus feedback. These are described in more detail in Figure 3.1.

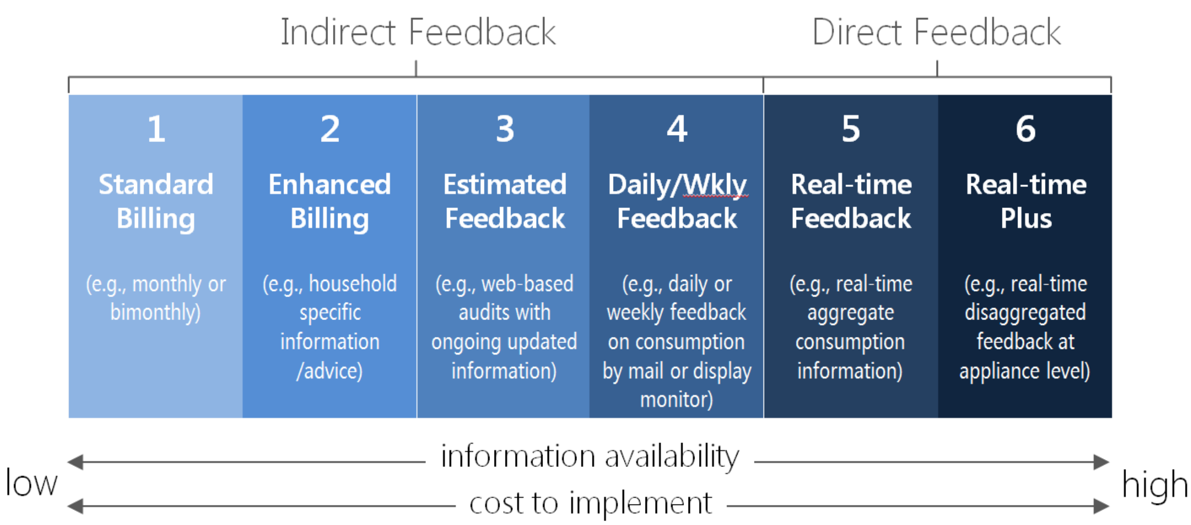


Figure 3.1: The EPRI feedback delivery spectrum (adapted from EPRI, 2009).

Finally, in the largest literature survey of residential feedback studies to date, Ehrhardt-Martinez *et al.* (2010) systematically reviewed 57 studies spanning two eras (1970s-early 80s and contemporary research) and nine countries. They synthesized past research findings using the feedback categorization schema developed by Darby (2000; 2006) and EPRI (2009) but specifically highlighted energy savings within each category. A subset of their results (for studies run between 1995 and 2010) are shown in Figure 3.2.

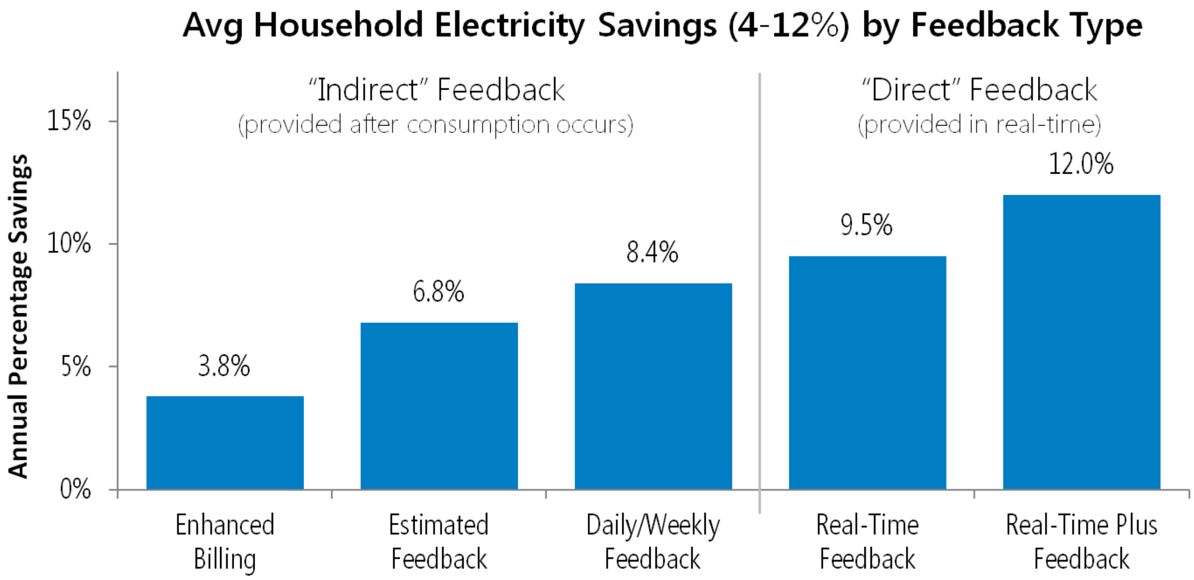


Figure 3.2: The average household electricity savings categorized by feedback type according to Ehrhardt-Martinez *et al.* (2010) based on a review of 36 feedback studies implemented between 1995 and 2010.

In pulling together the findings from the above summary studies (Darby, 2000; Abrahamse *et al.*, 2005; Fischer, 2008; EPRI, 2009; Ehrhardt-Martinez *et al.*, 2010), we can begin to observe effective (and not so effective) feedback designs. In those cases where no savings were found, the feedback occurred too infrequently (*e.g.,* in the form of a semi-annual bill update), was too unobtrusive, or the homes themselves were already low consumers. Designs that performed best provided computerized feedback (rather than, say, augmented paper bills) with multiple feedback options (*e.g.,* consumption over various time periods, comparisons, additional information like environmental impact or energy saving tips), were updated frequently (daily or more), were interactive (*e.g.,* the device provided configuration options or user could "drill-down" into data), were clearly and simply presented, and/or were capable of providing detailed, appliance specific breakdown of energy usage. Interestingly, providing direct financial incentives for consumers to drive energy reduction had little lasting effect: consumption reverted to its previous levels once the incentive was removed. This phenomenon highlights one of the major deficiencies in the current literature—few have studied the underlying cause of behavior change influenced by feedback technology nor its longitudinal impact.

Though feedback has great potential, simply revealing behavioral data, however, does not guarantee positive change or uniformly improve performance. As Latham and Locke (1991) state, "feedback is only information, that is, data and as such has no necessary consequences at all." Other factors such as age, the cost of energy, home ownership, income level, and family size may affect feedback's effectiveness. For example, feedback is not as effective for households where the cost of energy is proportionally low with respect to income (Geller *et al.*, 1982).

3.2 COMPARING APPROACHES ACROSS DISCIPLINES

We now focus more explicitly on studies of eco-feedback technology across the two primary disciplines involved in this research: environmental psychology and HCI/Ubicomp. We review literature in both fields to uncover differences in their approaches, treatments, and evaluations. The goals are to: (1) tease out what environmental psychology can offer to HCI; (2) better understand the theories and methodologies employed in studies of eco-feedback technology in both disciplines; and (3) uncover open areas of investigation that HCI and environmental psychology may be able to collaboratively pursue. Note that this research was conducted in the spring/summer of 2009; consequently, newer publications in either field are not represented.

From HCI/Ubicomp, we draw upon papers primarily from the CHI, Ubicomp, and Persuasive conferences and related workshops. We found 139 papers related to both HCI and the "environment" or "sustainability." Our corpus includes 58 workshop papers, 36 full papers, 32 papers found in extended abstracts (*e.g.,* demos, works-in-progress, alt.chi), and 13 short papers, journal or magazine articles. Roughly 44% of these papers were published in 2009 and 92% were published in the last three years. Of the 139 papers, 56 were related to eco-feedback technology—44 of these provide a unique eco-feedback artifact, while the rest are essays. If an artifact was published more than once, we removed redundancies in favor of full papers.

Our environmental psychology survey draws primarily from journals in psychology and sociology, such as the *Journal of Environmental Psychology*, *Journal of Consumer Research*, *Journal of Social Issues* and *Journal of Applied Social Psychology*. We also looked at the papers mentioned in three well-known surveys of energy feedback studies (Darby, 2000; Abrahamse *et al.*, 2005; Fischer, 2008). We found 82 papers related to the effects of feedback on environmental behaviors including recycling, transportation and home resource consumption (*e.g.,* gas, water, and electricity). Given the long history in environmental psychology of exploring eco-feedback, many of these studies were conducted before technology was seen as a practical feedback tool. Thus, most of these studies did not use eco-feedback *technology* in particular but rather other forms of feedback such as bill designs, media campaigns, pamphlets, and home audits. Much of this work is used in the next chapter to inform our discussion of the behavioral models and motivations techniques used in environmental psychology to encourage proenvironmental behavior. Here, though, we focus solely on the 12 studies in environmental psychology that did use eco-feedback *technology* (often referred to as “computerized feedback” in this literature).

In the next few sections we compare the 44 HCI eco-feedback papers with those from environmental psychology. An overviewof those papers that include an evaluation of their eco-feedback technology is shown in Table 3.1. A full list of the publications used in this comparative literature review is available in Appendix A.

		Environmental Psychology	HCI
	Field studies/Total studies	10/12	8/27
Field Studies	Average number of participants in field studies	210	11
	Average number of field study conditions	3.6	1.8
	Average field study length (including baseline)	15.5 mos	2.5 wks
	Average field study length (excluding baseline)	7.15 mos	2.5 wks
	Number of field studies that collected baseline data	9 (90%)	0 (0%)
	Average difference in consumption after feedback introduced in field studies	-18%	-10 liters in Kappel and Grechenig (2009), “marginal increase” in recycling in Holstius *et al.* (2004).
	Number of field studies that reported qualitative data	6 (60%)	6 (75%)
All Studies Reviewed	Number of studies that included eco-feedback interface screenshot	6 (50%)	23 (85%)

Table 3.1: A summary of the eco-feedback studies found in the environmental psychology literature vs. the HCI literature. See Appendix A.

3.2.1 Treatment of the Eco-Feedback Technology

The most striking contrast between the HCI and the environmental psychology literature is the emphasis (or lack of emphasis) on the visual design of the eco-feedback interface itself. Although both disciplines are ostensibly interested in understanding the role of feedback technology in changing behavior, environmental psychology has largely focused on the effect of the feedback intervention itself while HCI has concentrated on the production of the eco-feedback artifact and rarely on conducting field studies to actually study behavior change. This discrepancy largely reflects core orientations of the two fields.

Indeed, *only half* of the environmental psychology papers even provide a graphic of their eco-feedback interface. In several cases, the descriptions of the interfaces were only a few sentences long and no visuals were provided in the papers (*e.g.,* Sexton *et al.*, 1987; van Houwelingen and van Raaij, 1989). Figure 3.3 shows the two most commonly reported designs: (1) a simple LCD display, and (2) a bar or line chart showing a breakdown of usage on a PC, with some amount of historical data available for self-comparison. Almost all (10/12) of the devices used were semi-interactive, but interactions were often limited, for example, to pressing a button that would cycle through statistics like the current day's electricity rate or the amount of the last month's bill (*e.g.,* Sexton, 1987).

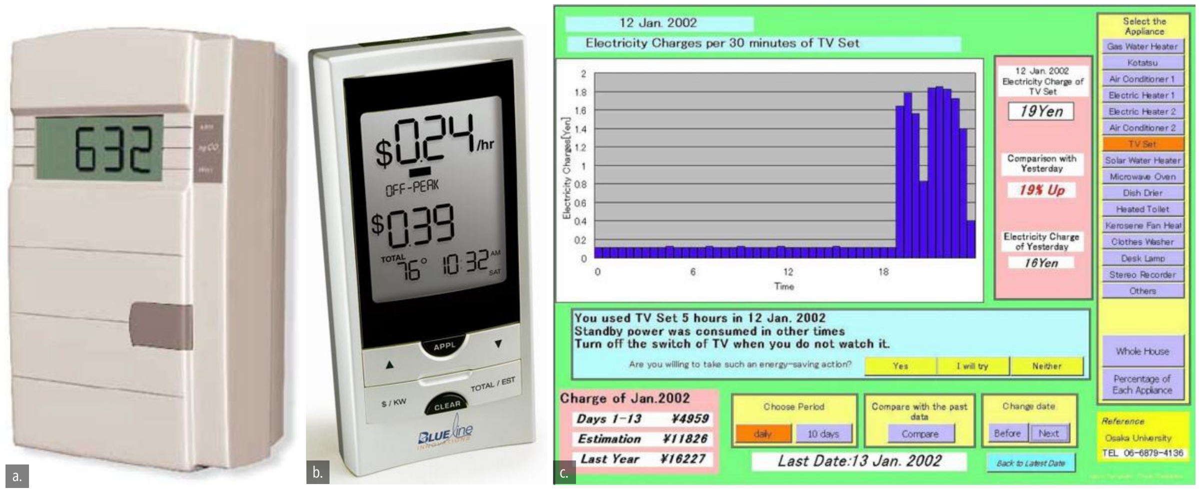


Figure 3.3: Some examples of displays used by environmental psychologists (and related disciplines) in the longitudinal behavioral trials. (a) A simple LCD display from Keirstead, 2007. (b) A more sophisticated LCD display used in Mountain, 2006. (c) The disaggregated electricity time-series display used in Ueno *et al.*, 2006.

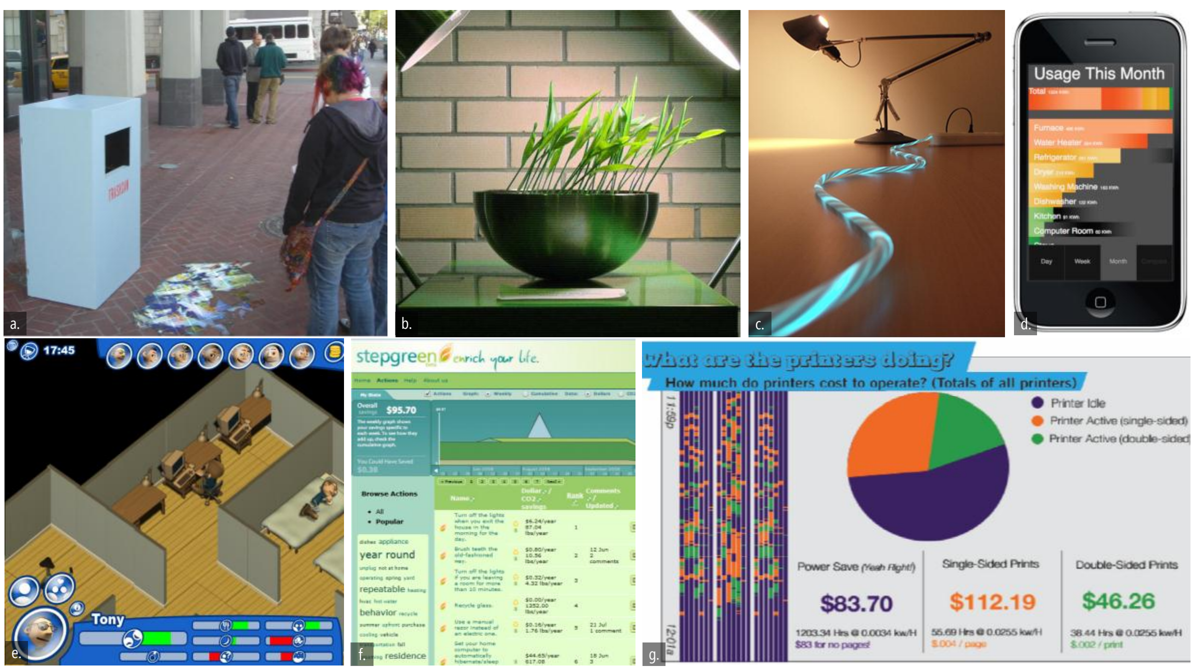


Figure 3.4: Example HCI eco-feedback systems: (a) JetSam: uses a camera and a projection system to project the inside of a trashcan outwards (Paulos and Jenkins, 2006). (b) The Infotropism display uses sensors and living plants to provide feedback about recycling and waste disposal (Holstius *et al.*, 2004). (c) Power-Aware-Cord: ambient energy usage display (Gustafsson and Gyllenswärd, 2005). (d) WattBot: mobile phone home energy feedback (Petersen *et al.*, 2009). (e) ThePowerHouse: resource eco-feedback in a virtual game environment (Bang *et al.*, 2006). (f) Stepgreen: proenvironmental behavior tracking social website (Mankoff *et al.*, 2007b). (g) Imprint: environmental impact of printing ambient public display (Pousman *et al., 2008).*

In contrast, the eco-feedback designs in the HCI papers were much more diverse and fully explained. Of the 27 HCI papers that provide some sort of study of their eco-feedback technology, only four papers do not disclose a screenshot of the interface. In addition, the studies employed a range of presentation mediums for their feedback including: ambient displays (*e.g.,* Arroyo *et al.*, 2005; Gustafsson and Gyllenswärd, 2005; Paulos and Jenkins, 2006; Pousman *et al.*, 2008), mobile phone applications (*e.g.,* Chapter 5; Petersen *et al.*, 2009), desktop games (*e.g.,* Bang *et al.*, 2007), and social websites (Mankoff *et al.*, 2007b)—see Figure 3.4.

Unfortunately, many of the eco-feedback designs in HCI do not link back to work in environmental or behavioral psychology. In our survey, less than half of the HCI eco-feedback papers referenced behavioral psychology literature and 58% referenced environmental psychology literature. Even more dramatically, no study in environmental psychology referred back to HCI. This represents a profound gap between disciplines. Interestingly, one author McCalley (*e.g.,* McCalley and Midden, 2002) has published in both fields—having published at both the Persuasive conference and journals in psychology and energy. Perhaps a future goal for HCI should be to initiate collaborations with environmental psychologists.

3.2.1.1 Discussion of Treatment

The primary motivation of eco-feedback technologies in both disciplines is to promote proenvironmental behaviors. Despite the relatively simple interfaces and lack of focus on design, the environmental psychology studies have achieved impressive results, a finding which should be cause for reflection by eco-feedback researchers in HCI. HCI researchers/practioners should ground their designs in the basic principles uncovered by environmental psychology. They can then apply the unique methodologies and approaches found in HCI (*e.g.,* user centered design) to further the design of eco-feedback technology.

Although the environmental psychology studies show that eco-feedback can reduce consumption, they do not clarify the extent to which this impact is based on specific design elements. Considering only the designs that appeared in the environmental psychology studies, we can see questions that HCI researchers are well-suited to study: How important is it that eco-feedback be even minimally interactive? What types of information and presentation mediums are most effective (*e.g.,* graphs vs. abstract ambient representations)? To what degree does the physical placement and access to the device impact its overall effectiveness? Answering these questions should allow us to identify how environmental psychologists may improve on the advances they have already made.

3.2.2 Consumption Targets of Eco-Feedback Technology

Eco-feedback technologies have been developed to target many types of consumption. The most common target is residential electricity usage: 41% of the papers in HCI and 92% of the papers in environmental psychology. This emphasis is both a reflection of the impact that electricity usage behaviors have on the environment as well as the ease with which energy usage can be automatically sensed.

As a field partially composed of computer scientists and designers, HCI researchers often have the resources to construct both their own novel sensing systems as well as their own feedback interfaces. HCI has also developed techniques to test and iterate on prototypes for exploring interactions and interfaces independent of the current state of technology (*e.g.,* Wizard-of-Oz evaluations). As such, HCI has explored eco-feedback technologies for a larger set of behaviors than have been studied in environmental psychology. We found 20 HCI papers on eco-feedback for electricity, four on water, four on transportation, four on carbon tracking, three on garbage and recycling behaviors, three on the environmental impact of product purchases, two on paper usage and one on eco-feedback for a virtual game world.

3.2.2.1 Discussion of Consumption Targets

The HCI studies have shown that people are open to new types of eco-feedback for behaviors outside of energy usage. One role for HCI is then to challenge the limitations of current eco-feedback technologies by envisioning and exploring novel consumption targets for environmental behavior change.

3.2.3 Study Methodology

Another important distinction between the two disciplines is in study methodology (Table 3.1). HCI researchers have largely focused on laboratory studies or qualitative field studies of eco-feedback technology. Although behavior change is often reported as the primary motivation for these projects, the emphasis tends to be on the artifact itself rather than its effect on behavior. This is not to say that the designs are not evaluated. Of the 44 eco-feedback technology papers from HCI, only 17 of them do not provide some sort of user evaluation of their designs (and 9 of these were workshop papers).

The HCI laboratory studies tend to be informal in nature, seeking feedback about understandability, aesthetic, and perceived usefulness (*e.g.,* Arroyo *et al.*, 2005; Gustafsson and Gyllenswärd, 2005).

For example, a Wizard-of-Oz lab study comparing three visualizations of the Power-Aware cord (Figure 3.4c) found that 13/15 participants understood the feedback without explanation, but that there was a tension between two different designs (pleasing vs. informative) (Gustafsson and Gyllenswärd, 2005). As the authors state in the paper, "*At this stage, the Power-Aware Cord is meant to be a conceptual design statement, mostly used to test people's reactions and provoke thoughts around the area of energy consumption."* This is a common approach taken in emerging areas of HCI. It is also consistent with the principled HCI tradition of iterative design, since the laboratory offers a rather low-cost means of receiving feedback about a design idea or preliminary prototype.

With respect to field studies, we found 8 papers in the HCI literature that conducted field studies of their eco-feedback technology, lasting between 1 to 4 weeks with an average of 11 participants. Of these studies, 4 reported behavior change data (Holstius *et al.*, 2004; Kim *et al.*, 2009; Kappel *et al.*, 2009; Yun, 2009). However, none of the studies included a control group that was not exposed to a feedback intervention, and only one study (Holstius *et al.*, 2004) collected any baseline data (of 1 week). In this respect, the study designs were better suited for collecting preliminary user feedback and conducting iterative design of the prototypes. The study in (Holstius *et al.*, 2004) was the most similar of the 8 to those found in our review of environmental psychology, although it was much shorter and did not include a control group that was not exposed to the intervention. The study evaluated the effect of an ambient plant display (Figure 3.4b) on garbage and recycling behaviors over a 2-week deployment in a university cafeteria. The researchers found no change in the amount of trash and a marginal increase in the amount of recycling; they also conducted interviews to uncover reactions to the design. Again, however, the focus was much less about quantitative experimentation but rather about subjective reactions to the feedback artifact.

In comparison to the HCI research, the studies in the environmental psychology literature were almost exclusively field studies (10/12), with one survey and one lab study. All of the studies looked at the effect of feedback on home resource consumption (either water, gas, or electricity). The field studies here included a much larger number of participants than did the HCI studies, ranging from 3 to 784 households (*avg*=210). The study with 3 households is the first known study of eco-feedback technology that we could find in our literature review: the Kohlenberg *et al.* (1976) light bulb study referenced at the start of this chapter. The largest studies (*avg*=414 households) were conducted in partnership with utility companies, which allowed researchers access to a large pool of data. Every study included a control group that did not receive an intervention, and all but one of the field studies collected baseline data. Few papers discussed the actual design process of their eco-feedback interface.

Only one of the environmental psychology studies was a controlled lab study (McCalley and Midden, 2002), but it offers a contrast to the HCI literature because it included a much larger sample size (N=100) and tested several different feedback conditions on behavior. A more typical study design from the environmental psychology literature was conducted by van Houwelingen and van Raaij (1989) and examined the impact of multiple intervention conditions on natural gas consumption. Interventions included electronic feedback, less frequent external feedback, self-monitoring, and information only. The study lasted three years, with one year each of baseline data collection, intervention, and post-intervention data collection. Results showed that all intervention conditions reduced consumption, with the electronic feedback condition being the most effective (a 12.5% reduction). Perhaps most interesting was that this reduction in natural gas usage did not last for the one year post-intervention period—in fact, there was no significant difference between the experimental and control groups after the interventions were removed. Thus, the feedback seemed to only have an effect during the period it was given. No long term habit formations were found.

3.2.3.1 Discussion of Methodological Findings

Researchers in HCI and environmental psychology have approached the design and evaluation of eco-feedback technology differently. The environmental psychology papers establish rough guidelines about how much baseline and intervention data studies need to collect in order to measure behavior change. In contrast, HCI offers techniques for iterating on feedback designs, particularly with respect to understandability, usability, and aesthetic. The styles of evaluation used in HCI are particularly important to employ before time and money are invested in extended behavioral change evaluations.

Both evaluation approaches are valuable, but the disciplines can also learn from each other. For HCI researchers, if our goal is to study behavior change, the environmental psychology literature demonstrates the importance of rigorous comparative controls, whether this is through improved collection of baseline data or the inclusion of control groups who are not exposed to an intervention. HCI does not, as yet, have a culture of longitudinal behavior studies—at least for eco-feedback technology.

This prompts the question: what incentives do HCI researchers have to conduct these sorts of studies and *should* it even be a goal? If not, then what is our goal in evaluating eco-feedback technology? Is it enough to demonstrate that a technology is usable and engaging, at which point we hand it off to psychologists or companies (*e.g.,* utilities) to conduct larger and more formal behavioral studies? Based on our survey, eco-feedback researchers in HCI have yet to reach a definitive consensus on these issues.

3.2.4 Summary of Comparison

This comparative survey has exposed differences in HCI and environmental psychology in terms of both goals and methodologies. Despite the long history of research in environmental psychology, we have identified areas that HCI is particularly well-suited to explore, and we expand on this opportunity in the next section.

3.3 DISCUSSION

We have helped uncover findings in environmental psychology that may be relevant to HCI and, at the same time, suggest where HCI offers the strongest contributions to the area of eco-feedback technology. Perhaps most importantly, we have started a conversation that may help bridge researchers in both fields. The most prevalent behavioral models and motivation techniques used in environmental psychology present a rich design space that can ground HCI research. Here we discuss some implications for future eco-feedback research and design.

3.3.1 Design Implications

Our analysis has highlighted some of the more salient design factors that need more exploration. These include the frequency with which a feedback system updates, the measurement units or other representation of consumption that are most appropriate to present, the level of granularity of the data (*e.g.,* do users see data from each appliance or the whole house), the accessibility and medium of the information (*e.g.,* push vs. pull, or an ambient display vs. a webpage), and the ability to make comparisons (either with one’s past behaviors or the behaviors of others). These various design attributes have yet to be fully investigated in either HCI or environmental psychology, although Egan (1999) and Fitzpatrick and Smith (2009) offer a good start. We pursue this further in Chapter 4.

3.3.2 System Development and Evaluation

In HCI it is rare to see field deployments on the scale of those conducted in the environmental psychology community. Although behavior change may be the ultimate goal of eco-feedback technology, it is clearly one that requires large amounts of time and resources to properly investigate. While this may be seen as a limitation of the HCI evaluation methodologies, we offer that this is not a detriment, but simply a difference. HCI has developed tools that allow us to explore aspects of eco-feedback technology that are not yet feasible for long-term deployments. Rapid prototyping, low-to-medium fidelity prototyping, and Wizard-of-Oz can be used to envision and study novel eco-feedback designs that circumvent technological limitations. Indeed, we see a role for HCI in providing eco-feedback designs that have been evaluated on merits such as evocativeness, engagement, understandability and usability. Even three-to-four week pilot studies are important in demonstrating potential. Those designs that seem particularly effective may then be handed off or evaluated collaboratively with environmental psychologists.

For testing ideas, the laboratory offers a context to evaluate understandability, aesthetics, and feelings towards the design. For higher fidelity prototypes, field deployments are more appropriate. Although the information presented in eco-feedback technology is intrinsically tied to the data provided by the underlying sensing system, in some cases these limitations can be overcome by careful study design (*e.g.,* manual meter reading to update interfaces). This allows the HCI researcher to focus on the eco-feedback artifact itself rather than implementing a durable sensing system.

3.3.3 Targeting Feedback Behaviors

What specific behaviors should eco-feedback technology be attempting to impact? Gardner and Stern (2008) draw a useful distinction between two types of consumption behaviors: (1) *efficiency behaviors*, which are one-time actions that provide a lasting impact, such as buying a fuel-efficient vehicle, and (2) *curtailment behaviors*, which involve forming new routines to reduce environmental impact, such as taking the bus to work (see Figure 3.5). A large majority of the eco-feedback technologies we reviewed in both HCI and environmental psychology have focused on the latter, yet it may be worth focusing on both. Gardner and Stern contend that the energy saving potential of efficiency behaviors *far outweighs* the potential of invoking curtailment behaviors. For example, the installation of compact fluorescent lighting (CFL) could be much more effective than remembering to turn off the lights. It is thus critically important that designers understand the environmental behaviors that they are trying to motivate and to design around those behaviors. An eco-feedback technology for water need not simply visualize daily water usage but could also make specific recommendations about efficiency behaviors—for example, quantifying the amount of money that could be saved by installing a low-flow showerhead.

That said, installing more efficient appliances (or driving a more efficient car) makes them susceptible to the rebound effect (Berkhout *et al.*, 2000) where something is used more often simply because it is more efficient thereby offsetting its positive impact on the environment. With the rebound effect "the importance of the interplay between macro-level (*e.g.,* technological innovations) and micro-level factors (*e.g.,* knowledge of efficient use of technological innovations) becomes apparent" (Abrahamse *et al.*, 2005). So, even with efficiency behaviors, feedback is important as it can convey how the usage of a new technology affects the environment. For more information on rebound effects, see Berkhout *et al.*, (2000) or, more recently, for a discussion on Sustainable HCI research and rebound effects, see Kaufman and Silberman (2011).

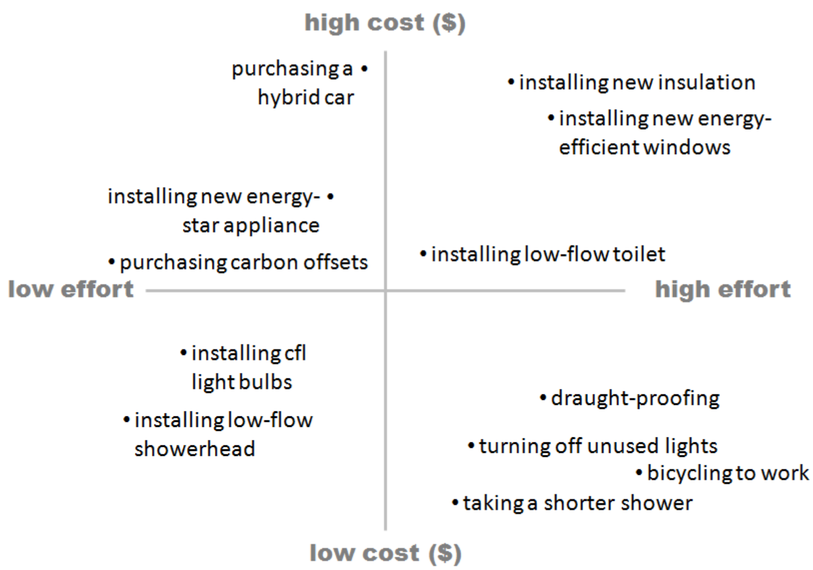


Figure 3.5: An example of cost/effort tradeoffs with respect to environmentally responsible behaviors. Curtailment behaviors tend to be low cost, but take relatively high effort to make routine. Efficiency behaviors range in cost and effort but can have similar, if not more, positive environmentally effects compared to their curtailment counterparts.

Pierce *et al.* (2010) extend the above categorization of energy conserving actions by integrating their own qualitative fieldwork examining home energy practices and preferences (Table 3.2). Here, their focus is particularly on defining a common vocabulary of energy-conserving interactions for HCI applications and interaction designers.

Cutting	*Powering off or putting in an extremely low-power state* (*e.g.,* powering off the television or putting it in a standby state)
Trimming	*Using a "lower" or more energy efficient setting when using a product* (*e.g.,* lowering the thermostat setting, or washing clothes on "cold" rather than "hot" temperature wash cycle)
Switching	*Using a more energy-efficient product in place of a product with similar but different functionality* (*e.g.,* using a ceiling fan instead of an air conditioner)
Upgrading	*Acquiring a more energy-efficient product to replace a product of the same time* (*e.g.,* replacing an older refrigerator with a more energy-efficient model).
Shifting	*Shifting use to a different time or place without necessarily reducing the total energy consumed by that product* (*e.g.,* washing clothes at night during off-peak hours of energy demand)

Table 3.2: Pierce *et al.*'s (2010) categorization of actions and strategies of energy conservation efforts and opportunities.

Finally, it should be noted that encouraging the purchase and installation of more efficient appliances and fixtures is not so simple because of the environmental impact of the disposal of the old good as well as the environmental impact of the manufacturing and delivery of the new good. Here, again, however eco-feedback can take lifecycle assessment into account when making recommendations and even suggest the most green manufactured product.

3.3.4 Learning and Feedback

Eco-feedback technology may have a lifecycle of usefulness. Van Houwelingen (van Houwelingen and van Raaij, 1989) emphasizes the role of learning in feedback: subjects learn the connection between the amount of resources they use and the consuming behavior. Darby (2000) argues that the effects of feedback are largely rooted in educational theory: feedback is an essential component in learning. Often, feedback provides information that individuals did not have before. If *learning* is one of the key benefits of eco-feedback, then how long does it sustain relevancy in a person's life? If a proenvironmental behavior is achieved, does the eco-feedback begin to lose its importance?

3.3.5 Large-scale Commercial Deployments

With the emergence and large-scale introduce of smart meters , eco-feedback technology may well become part of a common technological landscape. Millions of households will be able to view their home resource consumption data on their mobile phones and web browsers. This will provide great opportunities for the behavioral analysis of eco-feedback technology through massive AB testing. This uptake in the commercial sector also raises issues of privacy and trust, since eco-feedback technologies can collect vast amounts of information on personal habits.

3.4 CHAPTER SUMMARY

We have investigated the ways in which HCI and environmental psychology approach eco-feedback technology research. Our goal was to explore: (1) what HCI can learn from environmental psychology and (2) what the role of the HCI community should be in contributing to eco-feedback research. We believe that eco-feedback technology is a particularly ripe area for HCI and Ubicomp research because it often requires sensor building, information visualization, and novel interfaces and interactions. These are key areas of our expertise. HCI also offers a set of methodologies founded on rapid prototyping, user involvement, and iterative design that allows for design feedback early and often. As a community, however, HCI has yet to define how these methodologies should be used to evaluate the potential strengths of an eco-feedback design with respect to its ability to change behavior. We believe eco-feedback technology will soon play a major role in the ways in which we think about and act in the world. The HCI community should ensure that it is integral in helping shape the role of eco-feedback in the future.

The next chapter, Chapter 4, continues the interdisciplinary perspective introduced in this chapter but with a specific focus on how findings from environmental psychology and the behavioral sciences may be used to design more effective eco-feedback systems. Chapter 4 concludes by integrating these findings (and those from this chapter) into an eco-feedback design space, which serves both as a critical lens to evaluate existing eco-feedback systems as well as a guide to help design new ones. We also draw upon findings from this chapter to inform the design and evaluation of our eco-feedback designs presented in Chapters 5 and 9.

Chapter 4

The Design of Eco-Feedback Technology

In this chapter, we present an eco-feedback design space rooted in literature from multiple disciplines, including HCI, information visualization (InfoVis), environmental psychology and applied social psychology. We first introduce prevailing theories in psychology and sociology about what motivates action and behavior. We then enumerate a series of techniques that have been successfully applied in the behavioral science and environmental psychology literature, with a focus on how these techniques may apply to eco-feedback technology. Building on these discussions and incorporating both our own experience as well as findings from the HCI, Ubicomp, and InfoVis literature, we present a *design space* for eco-feedback. This design space includes eight dimensions and serves two main purposes: (1) to help in analyzing and critiquing existing designs and (2) to provide a process and foundation with which to approach building new designs, by understanding the tradeoffs of different points in the design space.

4.1 MODELS OF PROENVIRONMENTAL BEHAVIOR

Understanding why people engage in environmentally responsible behavior is a complex topic spanning many disciplines including education, economics, sociology, psychology, and philosophy. For example, researchers have explored how certain psychological variables correlate with environmental behavior such as: proenvironmental attitudes and beliefs (Dietz *et al.*, 1998; Dunlap and Van Liere, 1978; Scott and Willits, 1994) and personality traits (Pettus & Gilles, 1987; Schultz and Stone, 1994). Others have looked at contextual factors such as the convenience of the behavior (Gamba and Oskamp, 1994), an individual's abilities (Kantola *et al.*, 1983), and normative contexts.

Finally, others have looked at demographic variables such as age, gender, educational level, and income (Corral-Verdugo, 2002).

Although numerous theoretical models of proenvironmental behaviors have been developed and studied, no definitive explanation has yet been found (Kollmus and Agyeman, 2002). Still, these models offer insights into why people do act environmentally and thus they have direct implications for the design of eco-feedback technology. Even if it is not explicitly recognized, designers approach a problem with some model of human behavior, which affects the various design choices that imbue their design. Here, we highlight a few of the most commonly used models, which extend from three views of proenvironmental behavior. The first, *attitude models* consider the influence of knowledge and attitudes on behavior; the second, *rational-economic models* view environmental behavior primarily as driven by self-interest and cost-benefit analyses; and the third, *norm-activation models* emphasize social norms and pro-social motives as most important in influencing proenvironmental behavior.

4.1.1 Attitude Models

Perhaps the most common approach to modeling and predicting environmentally sustainable behaviors is through attitude-behavior models (Kurz, 2002). *Attitude models* assume that favorable attitudes translate into favorable behaviors (Shipworth, 2002). These models suggest that informing and educating people about environmental issues leads to proenvironmental behavior (which is also, perhaps, an implicit assumption amongst many eco-feedback designers). As such, the key issues become how to change people's attitudes towards environmental issues and to better understand the conditions under which such attitudes can be changed.

The two most popular attitude-behavior models are both by psychologists Ajzen and Fishbein: *theory of reasoned action* (Fishbein and Ajzen, 1975) and its extension the *theory of planned behavior* (Ajzen and Fishbein, 1980). The theory of reasoned action assumes that an individual considers consequences of a behavior before taking action. Thus, the role of *intention* is an important factor in determining behavior. The theory of planned behavior extends the theory of reasoned action by emphasizing factors external to the individual (*e.g.,* situational factors that may influence an individual's perception of control). According to Steg and Vlek (2009), the theory of planned behavior has been successful in explaining various environmental behaviors from travel mode choice and household recycling to waste composting and the purchasing of energy-saving light bulbs. In both models, Ajzen and Fishbein maintain that people are essentially rational making "systematic use of information available to them" and are not "controlled by unconscious motives" (as quoted by Kollmus and Ageyman, 2002).

A key issue with these models, however, is that any number of other factors may also influence behavior, so there is not always a strong relationship between attitudes and subsequent actions (Costanzo *et al.*, 1986). "One of the paradoxes of the psychology of environmentalism is that citizens generally hold preservation attitudes but routinely engage in environmentally unfriendly actions, such as driving to work instead of using public transportation" (Eagly and Kulesa, 1997). For example, researchers have found that people who cite conservation as the single most important strategy for averting an energy crisis are no more likely than others to engage in energy-conserving behaviors (Costanzo *et al.*, 1986). Gardner and Stern (1996, chapter 3) note that countries such as China and India, where long-standing religious traditions include strong proenvironmental beliefs do not have strong records of proenvironmental action. Despite these limitations, both the theory of reasoned action and the theory of planned behavior are considered influential behavior models in social psychology because of their clarity, simplicity, and ease with which they can be applied and studied empirically (Kollmus and Ageyman, 2002).

A more recent model, called the *model of responsible environmental behavior*, attempts to account for additional factors not originally addressed in Ajzen and Fishbein's theory of planned behavior (Hines *et al.*, 1986-1987). Through a meta-analysis of 128 proenvironmental research studies, Hines and colleagues proposed this model to emphasize the intention to act as well as situational factors that are conducive to such action (*e.g.,* economic constraints or social pressures). This model emphasized that *situational contexts* and both the knowledge of issues *and* of appropriate action were important factors in whether attitudes actually predicted behavior (Fransson and Garling, 1999). According to Stern (1999), a number of literature reviews of attitude-based behavior theories have shown that the predictive value of attitudinal variables for proenvironmental behavior largely depends on *context* and the amount of effort, expense, and inconvenience required to change the target behavior. Still, attitude remains a popular factor in most environmental psychology research and models. Kaiser *et al.* (1999) estimate that almost two-thirds of all environmental psychology publications incorporate attitude in one form or another so it is clearly worth attending to.

4.1.2 Rational-Economic Models

Rational-economic models assume that human behavior and decision making is regulated by a systematic process of evaluating expected utility—in other words, people act to maximize rewards and minimize costs. With respect to the environment, this model is often simplified to suggest that people will adopt environmentally responsible behaviors that are economically advantageous (though cost need not always be financial). Indeed, there is strong evidence that price plays an important role in stimulating conservation behavior. For example, the US government has found that an increase in gasoline prices corresponds to a drop in total freeway trips and a rise in demand for fuel efficient cars (Congressional Budget Office, 2008). Price is also used as a demand side management tool by utilities as high price signals have been shown to curb demand (Menon and Butler, 2006).

The rational-economic model, however, is predicated on the assumption that people understand whether a behavior or a device is cost effective, which is not always the case. Other environmental psychologists (*e.g.,* Gonzales *et al.*, 1988) have argued that tying proenvironmental behavior directly to economic parameters is not sufficient. One must also convince individuals that these benefits exist, are viable, and that they warrant action or changes in behavior. In addition, the rational-economic model tends to discount the effect of non-economic factors such as personal comfort, convenience, habit, and social norms (Yates and Aronson, 1983). Finally, in some cases, price simply cannot be significantly manipulated to change behavior. For example, dramatically increasing the cost of water quickly becomes an ethical issue as noted in Chapter 2.

4.1.3 Norm-Activation Models

Unlike the models above, which assume that behavior is regulated by reasoned and rational thinking, *norm-activation models* are based on the premise that moral or personal norms are direct determinants of pro-social behavior. Proenvironmental actions are often considered pro-social because they involve collective or community goods and the recognition that personal behaviors can affect others as well as future generations. A potential contradiction, then, in a rational choice model is that an optimal choice for the self-interested "rational actor" may not be optimal for the collective. Schwartz's norm-activation model (Shwartz, 1977) suggests that proenvironmental behavior can be stimulated if a person is aware of the negative consequences of his/her behavior on others and ascribes some amount of responsibility for taking ameliorative action. Thus, norm-activation models differ from rational-choice models in two important ways: (1) they recognize that behavior may be rooted in altruistic values and (2) that personal norm activation (*e.g.,* moral obligations) may trump subjective perceptions of utility (Staats *et al.*, 2004). Schwartz's norm-activation model and derivatives have been successfully applied to a variety of environmental behaviors including recycling, off-road vehicle use, and willingness to pay for eco-friendly products (Vining and Ebreo, 2002; Stern, 2000b).

Stern *et al.* (1999) extend Schwartz's norm-activation model with the *value-belief-norm theory* of environmentalism, which applies a similar value-based logic to a range of values such as curiosity, personal achievement, and feelings for wildlife. In this way, behaviors are activated not just in regard to other persons (who would suffer from environmental damage) but also in regard to the self and non-human species.

4.1.4 Synthesizing Models

Given the complexity of human behavior, it is likely that each of the models above have some relevancy and that a multitude of factors should be considered when designing an eco-feedback system. In *What Psychology Knows about Energy Conservation*, Stern (1992) argues that psychology research generally supports a multistate causal model to determine environmentally relevant behavior (Table 4.1). In Table 4.1, each variable acts as a possible influence on the variables listed below. Note the two feedback loops, which flow in the reverse direction: (1) learning occurs when outcomes such as energy bills affect specific attitudes and beliefs about energy savings, which could then subsequently change behavior and (2) processes such as self-justification or dissonance reduction (see, *e.g.,* Katzev and Johnson 1983 and 1984) can also feedback into higher levels of causality (in this case, self-justification is linked to changing general attitudes and beliefs). Stern also argues that this model helps explain the typical failures in finding relationships from one variable to another in past work; the issue is that there is often distance between the two variables (*e.g.,* from general attitudes to energy use) and that the intervening variables are usually left unmeasured. Stern's model is useful because it draws upon multiple determinants of behavior and attempts to provide some organizational hierarchy around how these determinants interact.

4.1.5 Models of Behavior Change

Psychologists have attempted to model not just determinants of a particular behavior but also how a person moves through stages of change to make that behavior routine. Many of the most

Self-justification

Learning

Level of Causality	Type of Variable	Examples
8	Background factors	Income, education, number of household members, religion, race, local temperature conditions
7	Structural factors	Size of dwelling unit, appliance ownership
	Institutional factors	Owner/renter status, direct or indirect payment for energy, rate structure
6	Recent events	Difficulty paying for energy bills, experience with shortages, fuel price increases
5	General attitudes	Concern for national energy situation
	General beliefs	Belief that households can help with energy problem
4	Specific attitudes	Sense of personal obligation to use energy efficiently
	Specific beliefs	Belief that using less heat threatens family health
	Specific knowledge	Knowledge that water heater is major energy user
3	Behavioral commitment	Commitment to cut household energy use by 15%
	Behavior intention	Intention to install a solar heating system
2	Resource-using behavior	Length of time air conditioner is kept on
	Resource-saving behavior	Insulating attic, lowering winter thermostat setting
1	Resource use	Kilowatt-hours per month
0	Observable effects	Lower energy costs, elimination of drafts, family quarrels over thermostat

Table 4.1: A high-level causal model of environmentally relevant behavior from Stern (1992) and Stern (2000a). Note that variables at each level of causality have the potential for direct influence on variables at each lower numbered level.

prominent behavior change theories have emerged from health psychology (*e.g.,* addiction studies) rather than environmental psychology. Prochaska's transtheoretical model (TTM) of behavior change (Prochaska and Velicer, 1997; Prochaska and DiClemente, 2005) is, perhaps, the most dominant model in the health behavior change literature. The TTM models change as a process involving progress through a series of stages including: precontemplation, contemplation, preparation, action, and maintenance/relapse/recycling. Prochaska's model is useful in that it identifies and emphasizes different stages in the behavior change process and underscores the steps necessary to move from one stage to another. Although TTM has largely been applied in the health behavior change literature, some recent work has looked at its application to proenvironmental behavior (He *et al.*, 2010).

It is not clear if behavior change models from the health literature can be wholly applied to proenvironmental behaviors. For example, does a person move through the same stages of behavior change in the Transtheoretical Model (Prochaska and DiClemente, 1986) when trying to quit smoking—a behavior that is clearly in their best self-interest to stop—compared to an environmental behavior, such as trying to eliminate wasteful energy usage? Regardless of these contextual differences, the behavior change literature offers a rich corpus of both behavior change techniques and behavior change theories, which should be investigated further.

4.1.6 Relating Models to Eco-Feedback Technology

The discussion above highlights some of the predominant theories of proenvironmental behavior in environmental psychology. It is not meant to be a step-by-step guide on which to base eco-feedback designs but rather an attempt to highlight the complexities and nuances underlying environmental behavior. Eco-feedback designers, whether conscious of it or not, imbue their designs with some theory of human behavior. For example, an implicit assumption often underlying the design of eco-feedback technology is that the presentation of information, particularly at a time of local decision making, is enough to provoke environmentally responsible behaviors. However, *how* the technology presents this information is fundamentally based on how the designer believes humans behave and react. It is important, then, to begin questioning and exposing the theories used in eco-feedback designs in our research and, when possible, to relate them back to work in environmental psychology.

Subscribing to one model versus another could result in strikingly different choices about the type and presentation of information. A design based on the norm-activation model should be value-centric: for example, feedback combining water usage data with updates about wildlife in a local watershed may invoke an altruistic response. In contrast, a design based on the rational economic model may stress the cost savings of a low-flow showerhead. The models are also useful in uncovering behavioral variables for eco-feedback technology to explore. That is, environmental psychologists have spent much effort examining different predictors of environmental behavior and building models around such predictors (*e.g.,* see: Stern, 2000b; Yates and Aronson, 1983; and Kollmus and Agyeman, 2002). These factors are worth attending to in eco-feedback designs.

Finally, some models, such as Prochaska's TTM are useful in underscoring not just the prerequisites of behavior change but the process necessary to fully adopt a new behavior (or change an existing one). In this way, future eco-feedback technologies could attempt to adapt their visualizations and messages to support different stages of the behavior change process.

4.2 MOTIVATORS AND INHIBITORS TO CHANGE

4.2.1 Intrinsic and Extrinsic Motivation

People are motivated to act for a variety of reasons; these reasons may be internal (*e.g.,* engaging in an activity because it is enjoyable or out of a personal commitment to excel) or external (*e.g.,* acting one way because of a bribe or the fear of being surveilled) (Ryan and Deci, 2000). These two categories of motivation, internal and external, are referred to as *intrinsic* and *extrinsic* motivation in psychology. In a range of studies exploring the two, Ryan and colleagues found that people who were intrinsically motivated had more interest, excitement and confidence relative to those that were externally controlled for an action. This was the case even when both groups had similar perceived levels of competence and self-efficacy. Furthermore, behaviors that were externally motivated (*e.g.,* by the use of financial incentives) often cease soon after the reinforcement ends—thus, rewards or feelings of guilt do not help create the type of high quality (internalized) motivation that lead people to take responsibility for their behavior (Osbaldiston and Sheldon, 2003).

Self-determination theory (Deci and Ryan, 1985) posits a process with which extrinsic motivational factors become internalized. De Young (2000) also argues that people may engage in environmentally responsible behaviors out of self-interest (*e.g.,* because it is personally satisfying to engage in those behaviors) and not for environmentally- or social-centric reasons. De Young offers three forms of intrinsic satisfaction derived from environmentally sustainable behaviors: (1) satisfaction derived from competence (feeling good about knowing what to do and doing it); (2) satisfaction from frugal, thoughtful consumption (not feeling wasteful); and (3) satisfaction from participation in a community (feeling part of a larger effort).

4.2.2 Sense of Control

A person is more likely to engage in environmental behavior if they believe that they can bring about change through their own behavior (Hines *et al.*, 1986-1987). Psychologists refer to this concept as the "locus of control." Individuals that believe that their actions have little-to-no impact are considered to have an *external locus of control*–they believe that actions of powerful others (*e.g.,* God, government) create change (Shipworth, 2002). These individuals are less likely to engage in proenvironmental behaviors than those who believe that their actions can have an impact (those with an *internal locus of control*).

4.2.3 The Role of Dissonance

Cognitive dissonance theory states that when a person holds two beliefs or items of knowledge that are inconsistent, the person will experience cognitive dissonance and be motivated to reduce this dissonant state (Festinger, 1957). When an individual *performs a behavior* that is inconsistent with his/her beliefs, the usual method of dissonance reduction is an attitude change in the direction of the seemingly discrepant behavior (*e.g.,* an attitude change can justify the action) (Sherman and

Gorkin, 1980). Aronson (1969) showed that dissonance theory is most prominent when a person does something that violates their self-concepts. For example, engaging in a behavior that is in conflict with a person's understanding that s/he is a good, moral or competent individual creates dissonance that s/he will seek to resolve. Studies have shown that cognitive dissonance can promote changes in attitudes as well as behavior (*e.g.,* Aronson, 1969). Cognitive dissonance has also been used successfully in a number of applied situations from weight loss (Axsom and Cooper, 1981) to resource consumption reduction (Dickerson *et al.*, 1992).

4.2.4 Other Motivations

Emotions such as fear, sadness/pain, anger, guilt and regret can be effective motivators. For example, there is a large amount of research on the persuasive use of vivid imagery and fear appeals to motivate behavior (see, *e.g.,* Finckenauer, 1982 or Weinstein *et al.*, 1986). However, Paul Stern (2000a), a noted environmental psychologist, notes that using fear to motivate can be complicated and suggests that fear may either persuade people to take constructive action or to simply ignore the problem. These reactions depend on a wide range of personal and situational factors including: a person's belief in their vulnerability to the threat, their judgment of its severity, their awareness of what positive actions to take in response, and the belief that they can actually take such actions without undue cost. A review of media campaigns targeted at energy conservation found that scare tactics were much less effective than specific, useful information (Shipworth, 2000).

In addition, Reiss and Havercamp (1998) identified sixteen basic desires that guide nearly all human behavior including *acceptance*: the need for approval, *curiosity*: the need to learn, *saving*: the need to collect, *status:* the need for social standing/importance, and *tranquility*: the need to feel safe. Each of these desires could be leveraged in eco-feedback displays to encourage proenvironmental behavior.

4.3 TECHNIQUES TO MOTIVATE PROENVIRONMENTAL BEHAVIOR

While models of proenvironmental behavior provide us with a philosophical and/or theoretical basis with which to design eco-feedback systems, they do not offer specific strategies for changing behavior. In this subsection, we cover some of the most popular motivation/intervention techniques used in behavioral psychology (*e.g.,* see Geller *et al.*, 1990), and offer examples that show how they have been applied to environmental behaviors. We review feedback as a strategy, as well as other popular techniques that may be used in conjunction with feedback, such as providing information or incentives.

In a seminal book called *Promoting Energy Conservation: An Analysis of Behavioral Research*, Katzev and Johnson (1987) provide a three-prong taxonomy of techniques for promoting energy conservation (Table 4.2): (1) the use of *antecedents*, such as informational materials, prompt and persuasive campaigns; (2) the use of *consequences*, where energy conserving actions are followed by feedback or rewards/penalties; (3) and the use of *social influences* such as group contingencies, modeling and commitment techniques. Geller *et al.* (1990) extended these three approaches into 24 subcategories distilled from the behavioral science literature. In Table 4.3 below, we have extracted the techniques most relevant to feedback technology. Although Geller's "intervention agent" describes a person (or persons) who promote the desired behavior among other individuals, here we can think about the intervention agent being a computing system (*e.g.,* a smartphone, ambient display). For example, a goal need not be assigned by a person but rather could be automatically assigned by the feedback system to activate some desired performance in behavior.

Antecedent	**Information**	Campaigns to promote conservation via information (*e.g.,* pamphlets, letters, books)
	Prompts	Cues designed to elicit conservation by means of signs, posters, flyers
	Persuasion	Appeals to conserve by means of written or media-based persuasive campaigns
Consequences	**Feedback**	Response contingent presentation of energy conserving information (*e.g.,* via bills)
	Incentives	Response contingent monetary rewards, rebates, or other tokens for conserving
	Disincentives	Response contingent costs, inconveniences and penalties for failing to conserve
Social Influences	**Groups**	Presentations of consequences contingent on group performance
	Modeling	Exposure to people (live or videotaped) performing energy conserving behaviors
	Commitment	Using social compliance procedures such as commitment or foot-in-the-door.

Table 4.2: Katzev and Johnson's (1987) taxonomy of techniques for promoting energy conservation.

Geller notes that the impact of an intervention is a direct function of: (i) the amount of participant involvement elicited by the intervention; (ii) the degree of social support available to the participant; (iii) the amount of specific response information transmitted to the participant; (iv) the degree of extrinsic control exerted by the intervention; (v) the target individual's perception of autonomy or self-control regarding the behavior change procedures. In addition, some of these techniques are focused on catalyzing extrinsic motivation (*i.e.,* motivation that comes from outside the individual) rather than intrinsic motivation (*i.e.,* motivation that is driven by an interest and enjoyment in a behavior itself). For example, the threat of punishment and the promise of a reward are commonly cited as extrinsic motivators while curiosity and the inherent drive to seek out new challenges are cited as intrinsic motivators. Researchers hypothesize that extrinsic motivation can become internalized under certain conditions (Deci and Ryan, 1985). The effect of these techniques will be moderated by how they are delivered by the eco-feedback system and perceived by individuals (which will likely vary from individual to individual).

Antecedent	**Commitment**	A written or oral pledge or promise by a subject to behave in a specific way.
	Discussion	Bidirectional communication between agents to prompt behavior. Communication focuses on generating consensus regarding the behavior change technique.
	Written / Oral Activator	A written or oral communication that attempts to prompt or activate desired performance or behavior.
	Individual / Group Goal	A goal is set to reach a certain behavior by a certain time. This goal may be self-assigned or set by an intervention agent.
	Competition	An intervention which promotes competition between individuals or groups to see which person or group will accomplish the desired performance level first (or best).
	Incentive	An announcement to an individual or group in written or oral form of the availability of a reward that is dependent upon the occurrence of a desired behavior by the individual.
	Disincentive	An oral or written announcement to an individual or group specifying the possibility of receiving a penalty contingent upon the occurrence of a particular undesired behavior.
Consequences	**Feedback**	Presentation of either oral or written information to an individual or group concerning level of performance regarding desired or undesired behavior.
	Reward	Presentation of a 'pleasant' item/event to an individual emitting a desired behavior, or the withdrawal of an 'unpleasant' item/event from an individual for emitting a desired behavior.
	Penalty	Presentation of an 'unpleasant' item/event to an individual emitting an undesired behavior, or the withdrawal of a 'pleasant' item/event from an individual for emitting an undesired behavior.

Table 4.3: A subset of Geller *et al.*'s (1990) 24 different approaches to change behavior that are most relevant to feedback technology. Note that social influences from Katzev and Johnson's (1987) taxonomy are folded into individual antecedent and consequence strategies. Geller *et al's* approaches also further differentiate between incentives/disincentives from rewards/penalties in that, for example, an incentive is a promise of a reward while the reward is the actual presentation of a pleasant item or event.

4.3.1 Information

The most widely used means to promote proenvironmental behavior change is information (Staats *et al.*, 2004). Media campaigns, pamphlets, or websites are all examples of this approach. The assumption is that with better information people will act in more environmentally beneficial ways. However, various studies of informational programs have shown that simply presenting people with information on the benefits of proenvironmental behaviors typically results in only a marginal effect (Katzev and Johnson, 1987). To maximize information's transformative potential it must be easy to understand, trusted, presented in a way that attracts attention and is remembered, and delivered as close as possible—in time and place—to the relevant choice (Brewer and Stern, 2005).

Many conservation programs use high-level written or verbal messages, called prompts, to promote conservation (*e.g.,* "Use Energy Wisely"). Investigations into general prompting strategies have shown that prompting has limited influence on behavior but can be made more effective by improving specificity, timing, and placement (Geller, 1982). For example, Winett *et al.* (1978) showed that placing signs next to doorways with specific information about when and who should turn out the lights (*e.g.,* the last person leaving the room) resulted in a 60% reduction in the number of days when the lights were left on compared to signs that were placed above light switches and contained only general messages about saving energy. This is a particularly rich opportunity for eco-feedback technology, which could provide feedback proximal in location and time to the target behavior. That said, deciding on *how* and *where* to present eco-feedback is a research question within itself and will likely need to balance attentiveness, cognitive load, user motivation, information relevancy, and cost. Highly localized displays may perform best with respect to behavior change (*e.g.,* placed directly on water fixtures or electric appliances), yet the cost of deployment and aesthetically fitting into homes are major barriers.

4.3.2 Goal-setting

Another well-studied source of motivation is goal-setting, which operates through a comparison of the present and a desirable future situation (van Houwelingen and van Raaij, 1989). Individuals, groups, and external agents (*e.g.,* a coach) can all set goals. Locke and Latham (2002) summarized 35 years of empirical research on goal-setting and found that goals affect behavior primarily through four mechanisms: first, goals serve a directive function—they direct attention and effort toward goal-relevant activities; second, goals have an energizing function and, in particular, high goals often lead to greater effort than low goals; third, goals affect persistence; and finally, goals affect behavior indirectly as individuals use, apply, and/or learn strategies or knowledge to best accomplish the goal at hand.

According to Locke and Latham, the goal-performance relationship is strongest when people are committed to their goals. Two key factors affect goal-commitment: (1) the importance placed on attaining the goal and (2) belief that the goal can be attained (self-efficacy). The concept of self-efficacy is important in goal-setting theory and relates to *intrinsic* motivation. Locke and Latham refer to studies that show that people with high self-efficacy set higher goals than people with lower self-efficacy. And when goals are assigned (rather than self-set), those with high self-efficacy are more committed, find and use better task strategies to attain the goals and respond more positively to negative feedback than people with low self-efficacy. Finally, Locke and Latham describe feedback as essential to goal-setting as it allows one to track progress towards completing a goal.

Goal-setting has been successfully applied in some technology aimed at behavior change (*e.g.,* UbiFit: Consolvo *et al.*, 2008) but it has not been significantly explored in environmental HCI. There is evidence, however, that goal-setting is a valuable technique to stimulate environmentally responsible behavior, particularly when combined with feedback. For example, in a study of electricity use, Becker (1978) found that households that received a difficult goal and feedback about their performance conserved the most (15.1%) compared to a control group. Similarly, van Houwelingen and van Raaij (1989) found that goal-setting in conjunction with daily feedback about consumption reduced natural gas usage by 12.3%. Questions remain, however, about *how* goals should be set and *what* goal targets should be used in addition to the role of goals once initial goal targets have been met.

4.3.3 Comparison

A comparison between individuals or groups can be useful in motivating action, particularly when combined with feedback about performance. Even feedback that provides information comparing one's current behavior to past behavior has been shown to be effective (*i.e.,* self-comparison). The effectiveness of *social* comparisons in environmental psychology, however, has been mixed. Siero *et al.* (1996) conducted a study of energy consumption behavior at two units in a metallurgical company and found that the unit exposed to comparative feedback saved more energy than the unit who received feedback only about their own performance. However, studies by Haakana *et al.* (1997) and Egan (1999) show that while people are often interested in comparisons, they do not necessarily have an impact on their behavior. One complexity is that eventually a performance plateau is reached, beyond which point emphasizing improvement over historical performance or the performance of others may not be effective. In addition, convergence effects may exist where both efficient and inefficient individuals change their behavior to more closely match average performance. In this way, a net gain in reduction is only possible if those inefficient individuals reduce more than the efficient individuals increase.

Still, comparison can be a powerful tool. OPower[20], a greentech startup company based in Arlington, VA., provides analysis tools and novel graphics to utility companies to improve the information and presentation on paper bills. For example, bills contain a bar graph that compares the current consumer's last month's energy usage with their neighbors and *efficient* neighbors. In its first trial in Sacramento, CA, homes with OPower's modified bills reduced energy consumption by 2% over homes that continued to receive regularly formatted bills (LaMonica, 2009). OPower has continued to show 2-4% reductions in aggregate energy use among bill recipients across cities (Laskey and

[20] http://www.opower.com

Kavazovic, 2011). One way they deal with convergence effects is to use an injunctive message, in this case a smiley face, is enough to diminish the number of households who *increase* usage after observing that they use less than average.

Moving forward, social media, such as Facebook or Twitter, may be used to mediate realtime sharing and comparisons. This is a relatively new topic of research (*e.g.,* Mankoff *et al.*, 2007b), however, and is also perhaps one of the most underexplored aspects of motivating behavior change. Social networking sites have the potential to provide accountability and normative pressure to engage in proenvironmental behavior (*e.g.,* Goldstein *et al.*, 2008) including the incorporation of competitions, social comparisons, and public commitments. However, it's unclear who might be interested in this sort of social media use and how it might be implemented.

4.3.4 Commitment

A commitment is a pledge or promise to behave in a specific way or attain a certain goal. A person that expresses commitment increases the probability that s/he will pursue that behavior (Gonzales *et al.*, 1988; Katzev and Johnson, 1987). For example, Wang *et al.* (1990) found that a signed pledge to recycle led to a 47% increase in recycling compared to baseline data. Similarly, Pallak and Cummings (1976) used public commitment to promote gas and electricity conservation among households—the group committed to publicizing their results used 15% less natural gas and 20% less electricity than other conditions. The type of commitment a person makes, the person or group to whom the commitment is made, and whether the commitment is public or private are three factors that impact behavior. Questions remain about how eco-feedback may incorporate commitment tactics including how the interface itself queries for a commitment, how long this commitment is meant to last, and who the commitment can be (and should be) shared with.

4.3.5 Incentive / Disincentives and Rewards / Penalties

Although sometimes used interchangeably, incentives and disincentives are distinct from rewards and penalties. Incentives and disincentives are antecedent motivation techniques—they come *before* a behavior (Geller *et al.*, 1990). Rewards and penalties are consequence motivation techniques—they come *after* a behavior. Incentives have been used effectively to motivate a range of proenvironmental consumer behaviors from investments in home insulation to rebates for new energy-efficient home appliances. Incentives need not always be monetary; those incentives associated with status or convenience may also have important effects on proenvironmental behavior. For example, specially reserved parking spots for rideshare users have been shown to increase carpooling, and curbside pickup of recyclable materials has significantly increased recycling efforts (Stern, 1999).

Research into the effects of rewards have found that people respond to rewards even if they are nominal in nature (*e.g.,* an acknowledgement of positive behavior) and that the reward should be linked as closely with the target behavior as possible (Valente and Schuster, 2002). Previous research in persuasive health technology has shown that even providing an asterisk after the completion of a behavior is enough to elicit a positive response (Consolvo *et al.*, 2006). OPower bills "awards" smiley faces to those households that are efficient consumers (Laskey and Kavazovic, 2011). Eco-feedback designs may not be able to offer financial incentives unless paired with a utility company, but most certainly can rely on game-like reward elements (*e.g.,* points, levels, etc.) to promote behaviors (*e.g.,* see elements of Chapter 5, or Bang, 2007).

A challenge in applying incentives/rewards is knowing *what* and *how much* to offer for a given behavior. Stern (2000a) notes the difficulty in determining the "right" incentive to motivate cities and industrial manufacturing plants to reduce air pollution and that institutional constraints or mistrust in information can mitigate the effectiveness of incentives. Still, he argues that "prices and other tangible incentives are very important tools for behavior change." (Stern, 2000a).

4.3.6 Feedback

Many of the above motivation techniques require some sort of *feedback* to be effective (*e.g.,* goal-setting requires feedback about performance towards a goal). One of the best-established findings in psychology is the positive effect that feedback can have on performance (Becker, 1978). Feedback comes in two forms: *low-level feedback* can provide explicit detail about how to change or improve specific behavior (*e.g.,* the particular problems marked wrong on a math test helps identify trouble areas for students); *high-level feedback* is summative and can help improve performance towards a goal or in comparison to others (*e.g.,* obtaining a 'B+' in math class may motivate the student to seek an 'A' next semester).

A majority of research into the effect of feedback on proenvironmental behaviors has focused on home resource consumption. Fischer (2008) reviewed approximately twenty studies and five compilation publications from 1987 onward exploring the effects of feedback on electricity consumption and on consumer reactions, attitudes, and wishes concerning such feedback. She found that feedback resulted in typical energy savings of between 5 and 12% (though the absolute range was 0 to 20%). In cases where no savings were found, the feedback occurred too infrequently (*e.g.,* in the form of a semi-annual bill update), was too disconnected from the consumption behavior, or the homes themselves were already low consumers.

Although only 3 of the 20 studies reviewed by Fischer used computerized feedback (in contrast, for example, to redesigned bills), those studies resulted in the greatest change in energy consumption. In particular, she found that the most effective feedback interfaces contained multiple feedback options (*e.g.,* consumption over various time periods, comparisons, additional information like energy saving tips), were updated frequently, were interactive (*e.g.,* the user could “drill-down” into data), and/or were capable of providing detailed, appliance specific breakdown of energy usage. More work is needed to determine if these results translate to other forms of consumption or environmentally impactful behavior; however, these findings highlight the potential of eco-feedback technology. The effect of feedback on proenvironmental behavior is reviewed in Chapter 3 in more detail.

4.3.6.1 Framing Feedback to Influence Choice and Decision Making

Although feedback itself has been shown to be effective in changing behavior, the way this feedback is framed can impact behavior differently. For example, the way in which a choice is framed can influence the decision outcome. Tversky and Kahneman (1981) showed how individuals are more sensitive to losses than they are to gains even if the underlying proposition is the same. That is, individuals are more likely to take action to avoid or minimize a loss than they are to secure a gain of the same quantity. Tversky and Kahneman’s study framed a question to participants in two different ways, one as a choice between losses and another as a choice between gains. Participant responses reversed depending on the phrasing of the question even though the outcomes were the same. Further empirical work has found that losses are weighted about twice as strongly as gains—that is, the disutility of losing $100 is roughly twice the utility of gaining $100 (Thaler *et al.*, 1997).

Commonly, feedback interfaces reveal how much energy is being used contextualized within a historical frame (*e.g.,* a time series line graph visualizing the current day’s energy usage information). Given that humans are generally averse to losses, perhaps a better rendering of the data is how much energy (or money) is being lost *by not taking action* (*e.g.,* by installing more efficient appliances). Indeed, research by Yates and Aronson (1983) indicates that persuasive appeals can be made more effective by encouraging consumers to consider losses that result from the failure to adopt energy-conserving technologies. Modern feedback technology has the ability to calculate these losses extremely accurately and to render them in an evocative manner.

In many decision-making situations, people make estimates by starting from an initial value that is then adjusted to yield the final answer (Tversky and Kahneman, 1974). For example, estimating the amount of time it may take to get home by bicycling versus taking the bus involves taking into account past experiences with each transit mode (an initial value) and then extrapolating given the current context (*e.g.,* weather, distance to bus stop, traffic). Though it may occur often in a person's life, this is a rather complex calculation. When making a decision, individuals tend to fixate on certain types of information ("anchor points") rather than exhaustively searching for and processing all relevant information (Tversky and Kahneman, 1974). This has direct implications for the design of feedback interfaces—depending on how information is presented, decisions can be biased towards the initial anchor point. These biases can be significant: in Tversky and Kahneman's experiment, participant responses to quantitative questions would vary by 20% depending on an initial, random value that they were given. Indeed, in more realistic scenarios (*i.e.,* outside the laboratory), it has been found that when faced with uncertainty, the status quo or default option of a decision tends to be favored (Armel, 2008).

4.3.7 Relating Motivation Techniques to Eco-Feedback

The above section summarizes key motivation techniques that environmental psychology and the behavioral sciences at large have used to influence behavior. As is apparent from our summary, these techniques have a varying degree of effectiveness. When designing eco-feedback technology it is important to consider not just which motivation techniques to employ but what behaviors, in particular, a design is hoping to motivate.

Each behavior has its own set of contexts and constraints that impact behavior change. An individual considering bicycle commuting, for example, must have access to a bicycle, helmet, and lock; live within a reasonable distance of his/her workplace; plan an appropriate bicycle route; have access to a changing room and shower; and so on. One must also think about *why* the individual is considering bicycle commuting—is it for the exercise, for the reduction in CO_2 emissions, for the image it presents to co-workers, or is bicycling just an opportunity to be outside?

Thus, eco-feedback designers must think deeply about and study the particular behaviors they hope to change and/or motivate before building their prototypes. Ethnography is certainly one valuable approach here, surveying is another; both have been effectively applied in environmental HCI (*e.g.,* the formative studies in Chapters 5 and 6, and ethnographic studies in: Woodruff *et al.*, 2008; Chetty *et al.*, 2009). It is also critical to turn to environmental psychology to see which types of behaviors have been explored and what motivation techniques have been used (as we did in Chapter 3).

4.4 AN ECO-FEEDBACK DESIGN SPACE

Previous efforts have looked at articulating a set of design concerns for eco-feedback technology with a particular focus on residential energy consumption (Wood and Newborough, 2007; Pierce *et al.,* 2008, Fitzpatrick and Smith, 2009; Rodgers and Bartram, 2010; Sundramoorthy *et al.,* 2011 as well as my own work: Froehlich, 2009). The recency and popularity of such work demonstrates an identified need for structuring the eco-feedback design process, defining clear vocabulary, and framing and focusing future research into effective eco-feedback designs. Our design space builds on this past work but broadens it to include design factors relevant to all eco-feedback technology (not just that for the home). In addition, it integrates findings from a variety of fields including information visualization, the behavioral sciences, HCI, and environmental psychology (as described in this chapter as well as in Chapters 2 and 3).

To create our eco-feedback design space, we reviewed and synthesized the above sources to create a large list of design attributes related to eco-feedback technology. Two researchers then independently organized these attributes into higher level categories and subcategories via affinity diagraming. These categorizations were then discussed and merged into a single set. The final design space, shown in Figure 4.1, is broken down into eight high-level design dimensions, each of which has a series of sub-dimensions. The dimensions include how the eco-feedback data is manifested and visualized (*Display Medium* and *Data Representation*), how the data is accessed and interacted with (*Information Access* and *Interactivity*), how actionable the presented data is (*Actionability/Utility*), and motivational factors (*Social Aspects*, *Comparison*, *Motivational/Persuasive Strategies*). These dimensions are not entirely orthogonal; indeed, many intersect. However, the key is in how they help to structure the design process and for analyzing and comparing existing instances to aid in the development of new systems.

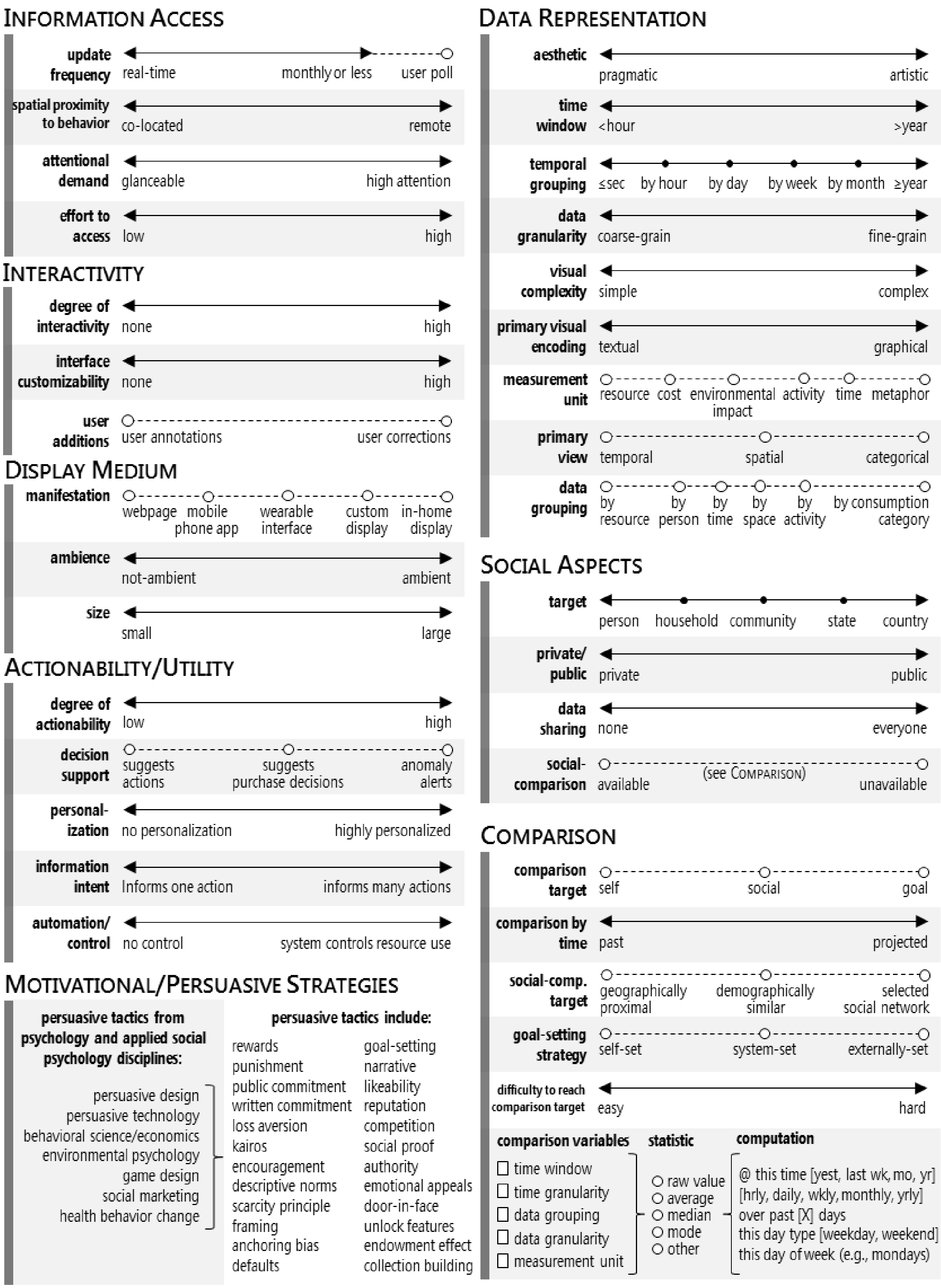


Figure 4.1: The eight dimensions of the eco-feedback design space (along with sub-dimensions).

This design space serves three goals: (1) to allow designers to approach the eco-feedback design process with a tangible structure that exposes assumptions underlying various eco-feedback techniques and provides a means to reliably compare the strengths and weaknesses of different design decisions; (2) to uncover underserved opportunities for eco-feedback and provide a structure for exploration of design possibilities; (3) to provide a *common vocabulary* with which to discuss and analyze eco-feedback designs. Below, we briefly describe each of the eight dimensions and their sub-dimensions.

4.4.1 Information Access

Information Access refers to *how* the eco-feedback information is accessed, how often it is updated, and the system's demands on attention.

Update Frequency: refers to how often the display is updated, from real-time to monthly (or even less frequently). The design space also includes a non-exclusive discrete option for user polling (*e.g.,* visiting a webpage). As previously mentioned, the frequency with which a feedback system updates appears to improve the link between action and effect and, therefore, increases an individual's consciousness about their action's consequences (Fischer, 2008). Several studies have demonstrated the benefit of frequently updated feedback to reduce consumption. Bittle *et al.* (1979) placed feedback cards that described the amount of kilowatts consumed the previous day into residential mailboxes. The feedback group used an average of 1-9% less electricity than the control group, which only received monthly bills. In a more recent study, homes that used a computerized feedback display of real-time electricity usage reduced electricity consumption by 12.9% (Dobson and Griffin, 1992). The ideal frequency of feedback is unclear, but new types of computerized feedback systems provide a level of flexibility in data presentation and access that was previously unavailable.

Spatial Proximity to Behavior: refers to the location of the display in orientation to the target behavior. Displays that are spatially co-located and updated frequently have the most potential to change behavior but at a cost of higher attentional demand. The location of the feedback may be highly localized (*e.g.,* on the appliance itself) or completely independent (*e.g.,* via an internet portal or paper bill). A single display may be positioned in a highly trafficked part of the home, for example, in the family room or kitchen. Feedback location is restricted by sensing capabilities and the cost of installation. Currently, localized displays tend to either be built into the appliance or part of the sensing assembly unit. Two recent studies show that linking energy consumption and source through localized displays is a promising direction. McCalley and Midden (2002) gave consumers immediate feedback about washing machine energy usage via an attached control panel and found a 21% reduction in energy use. Ueno *et al.* (2005) installed sensors for each home appliance and also monitored total electric power and gas consumption and found a 12% reduction in energy usage after system installation.

Attentional Demand: refers to the glanceability of the display. This is related to the *Ambience* sub-dimension in *Display Medium* but is different in that you can have a display with low-attentional demand that is not ambient.

Effort to Access: refers to how much work the user must do to access the information. The ideal display should try to minimize effort and yet balance user attention requirements. UbiGreen (Chapter 5), for example, visualizes transit usage information on the *background* of a mobile phone. Thus, the eco-feedback data is always available when the user is normally interacting with the phone (*e.g.,* to make a phone call or to send a text message). Of course, the user can also choose to specifically take out his/her phone to look at the eco-feedback data explicitly. In contrast, to view home energy information in Microsoft Hohm, the user must have a computer with access to the internet, needs to navigate to the Microsoft Hohm webpage, login and find an appropriate webpage detailing usage (a much higher effort to access data).

4.4.2 Data Representation

Data Representation refers to the visual manifestation of the eco-feedback information including its aesthetic, how the data is grouped, the type of measurement units displayed, and primary visual encodings (*e.g.,* graphical vs. textual). According to Fischer's (2008) eco-feedback literature review, very few studies have considered the role of graphic design or the format of presentation on behavior.

Aesthetic**:** refers to the appearance of the display, its look and feel and the tradeoffs between functionality and utility and art and beauty (Figure 4.2). We heavily borrow from Kosara (2007) here who distinguishes between two aesthetic approaches: pragmatic visualizations vs. artistic visualizations. Pragmatic visualizations analyze, synthesize and present information in a way that allows a thorough understanding of the data—Kosara notes that Card *et al.* (2010) describe this process as *knowledge crystallization*. Visual efficiency is a key attribute of pragmatism: produce visualizations that convey data as quickly and effortlessly as possible. In contrast, the goal of *artistic* visualization is primarily "to communicate a concern, rather than show data" (Kosara, 2007). The data is transformed and conveyed in a more interesting, artistic fashion such that it may not be immediately recognizable but still must be readily understood.

Pragmatic visualizations are more common and provide concrete quantitative information; however, they often require a ramp-up period to learn (*i.e.,* visualizations are learned interfaces). Artistic visualizations are more abstract by nature and can use visual representations that the consumer may find evocative but often at a cost of explicitness. For example, in UbiGreen (Chapter 5), we found that although users appreciated artistic metaphors that represented their travel activity, they also sought more precise information that would allow them, for example, to better compare their current performance to previous performances. More research is necessary to know when, where, and how pragmatic and artistic visual designs should be used.

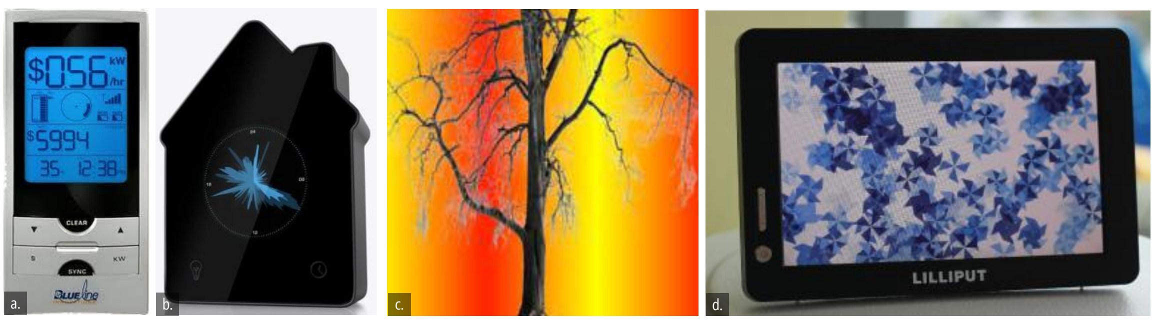


Figure 4.2: Different aesthetics: (a) The Blue Line Innovations PowerCost monitor is primarily text based and displays real-time electricity use in terms of cost and kWh.(b) the Energy Aware Clock by (Broms *et al.*, 2010) overlays energy usage onto a clock; (c) Holmes (2007) "7000 Oaks and Counting" visualization uses a tree metaphor to communicate energy flows in a building; (d) The Pinwheel design by Rodgers (2011) adds spinning pinwheels based on amount of energy used.

Time Window**:** refers to how much historic data is available to view and the time window used to calculate the data displayed by the eco-feedback system. For example, it is common practice now for home energy bills to provide a bar graph depicting the *last year* of usage broken down by month. In our own studies (Chapter 9), we have found that users particularly like being able to see temporal patterns corresponding to season as well as to compare usage for the current month to the same month last year. A *year* time window allows for these sorts of investigations (Figure 4.3a).

Figure 4.3: Different time windows: (a) A Seattle Public Utility electricity bill shows a bar graph of electricity usage over the past year (including the current month). (b) The Toyota Prius dashboard display shows mileage and regeneration information for the last 30 minutes. (c) Lucid Design Group's building dashboard shows electricity use, in this case, over the course of a day.

Temporal Grouping: refers to the temporal grouping of data (*e.g.,* by hour, by day, by week). In Figure 4.3a the t*ime window* is one year but the *temporal grouping* is by month while in Figure 4.3b the time window is 30 minutes but the temporal grouping is in five-minute intervals.

Data Granularity: refers to the granularity of data displayed on the screen. For example, for electricity eco-feedback, the finest granularity would be device/outlet level while the coarsest would be neighborhood (or larger) level; see Figure 4.4.

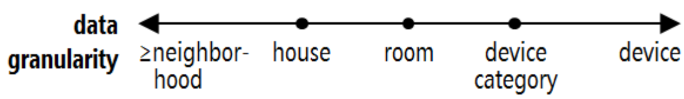


Figure 4.4: The data granularity design sub-dimension applied to home resource consumption.

Visual Complexity: refers to how busy the display seems. This aspect could also include the approachability/immediate understandability of the display.

Primary Visual Encoding: refers to the primary visual elements used to feedback information from textual to graphical. For example, the Kill-A-Watt display is completely textual whereas UbiGreen is completely graphical.

Measurement Unit: refers to the metrics used to measure and present usage. The design space includes the most common units: resource (*e.g.,* watts, kWh), cost, environmental impact (e.g, CO_2 emissions and how that affects the environment), activity (*e.g.,* number of times biked to work vs. drove), time (*e.g.,* length of a shower), metaphorical units (*e.g.,* the number of one gallon milk jugs used in last shower). Like many of the design dimensions, the choice of measurement unit is not just about understandability but also about identifying a presentation that the individual or household may find particularly motivating (*e.g.,* cost vs. environmental awareness). See Figure 4.5 for examples.

Figure 4.5: (a) General Electric's Ecomagination display uses cartoonish iconography to display energy consumption values in terms of dollars, tons of CO_2 and miles driven. (b) The Lucid Design Group Building Dashboard display uses metaphors in terms of gallon jugs and toilet flushes to convey water usage. (c) The Energy Detective (TED) can be set to display electricity usage in terms of cost or kWh; here the display is showing cost/hour.

Primary View: refers to the primary view used by the visualization, including temporal, spatial or categorical. For example, in Chapter 9, we present a variety of water usage eco-feedback designs including a time-series visualization (temporal), a blueprint-based visualization (spatial), and a bar graph visualization of water usage by fixture (categorical).

Data Grouping: refers to how data is grouped. For example, an eco-feedback display for electricity or water may group the data by consumption category (*e.g.,* different types of electricity devices or faucets vs. toilets, etc.) and by space (*e.g.,* which rooms use the most energy or water).

4.4.3 Interactivity

Interactivity refers to the degree with which the user can interact with and customize the eco-feedback display.

Degree of Interactivity: refers to the degree with which the display supports user-interaction from *none* to *high.*

Interface Customizability: refers to the degree with which the display can be customized from *none* to high.

User Additions: refers to the support for different types of user additions such as annotations or corrections of incorrectly sensed usage data (*e.g.,* for probabilistic sensing systems).

4.4.4 Social Aspects

Social Aspects intersects with *Motivational/Persuasive Strategies* and *Comparison* and yet Social Aspects deserves its own dimension because of the importance of social influences on behavior (*e.g.,* see social influences in Katzev and Johnson, 1987) as well as because it allows us to emphasize social context (private/public) and individual vs. social targets.

Target: refers to the intended target or targets of the eco-feedback display. Most past work has focused on feedback for individuals (*e.g.,* UbiGreen in Chapter 5), but feedback could also shape and inform group behaviors at the household level and beyond.

Private/Public: refers to whether the eco-feedback display was intended for private or public viewing. Private here need not simply mean designed for only a single individual viewer as there are different layers to privacy (hence, the spectrum).

Data Sharing: refers to *what* information is shared with others and *who* that information is shared with in the case that the eco-feedback display is not private to a single user.

Social-Comparison: refers to *who* and/or *what groups* are comparison targets. Note that this dimension is included here for comprehensibility but belongs in the *Comparison* subspace.

4.4.5 Display Medium

Display Medium refers to the physical form, size, and ambience of the display.

Manifestation: refers to the physical manifestation of the display. UbiGreen (Chapter 5), for example, is a mobile phone application for feedback on personal transit activities. In contrast, Chapter 9 explores water usage feedback displays that are meant to hang on a wall, fridge or other location in the home.

Ambience: refers to the ambient quality of the display. Ambient displays "are aesthetically pleasing displays of information which sit on the periphery of a user's attention" (Mankoff *et al.,* 2003). Oftentimes, ambient displays trade reduced user interaction for increased aesthetic emphasis (Skog *et al.,* 2003). For example, the Ambient Orb by Ambient Devices[21] maps incoming data into the color of a glowing orb (*e.g.,* if mapped to a particular stock, the orb glows green when the stock is rising and red when the stock is falling). In 2007, Southern California Edison tested the use of the orb's ability to affect peak energy use behaviors by installing 120 orbs that would glow green when the grid was underused (*i.e.,* when electricity was cheaper) and red during peak hours. They found a

[21] http://www.ambientdevices.com/products/energyorb.html

40% drop in peak-period energy usage (Thompson, 2007); however, it is unclear if this change persisted.

Size: refers to the size of the display medium and the data displayed therein. Size affects ambience, ability to discern at a distance, as well as how the display fits into different types of spaces and contexts.

4.4.6 Actionability/Utility

Actionability/Utility refers to how directly users can translate the data on the display into an action that appropriately reduces environmental impact. Like many of the dimensions from other subspaces, the dimensions here are subject to interpretation by the user.

Degree of Actionability: refers to how easy it is to view the eco-feedback display and know *what to do,* if anything, to reduce environmental impact. Degree of actionability can interact with other aspects of the design. For example, informing the user that they take longer showers than average is more actionable than simply telling them their overall household water use is higher than average. Note that degree of actionability may also be highly subjective; for example, if an Ambient Orb display glows red, household residents may have learned that this is because energy on the grid as at peak use, while a visitor may not have the contextual frame to make this inference.

Decision Support: refers to suggesting particular actions and purchase decisions to reduce consumption or address specific usage issues (*e.g.,* water leaks). Ideally, the decision support should be highly personalized and based on the low-effort actions on behalf of the resident. Few systems, if any, that we are aware of offer advanced decision support. Research suggests, however, that humans tend to assign disproportionate weight to information that is highly concrete and personalized (Borgida and Nisbett, 1977). Computerized feedback may be able to offer highly personalized recommendations tailored to particular sensed actions. For example, the system may be able to detect a malfunctioning water heater which is consuming excessive amounts of energy. In those cases, the system could, for example, provide links to more efficient water heaters that would be more economical in the long-term (with specific cost/benefit analyses).This is an important future direction and relates to shifting the cognitive effort from the user to the system.

Personalization: refers to the degree with which the display is personalized to individuals or individual households. This could include both the degree with which the decision support system is personalized as well as the adaptation of the visualizations to support different stages of use over time.

Information Intent: refers to the number of actions that the display is meant to inform. For example, the Toyota Prius display is meant to inform a few driving-related behaviors (*e.g.,* acceleration and braking behavior) while the disaggregated water usage displays presented in Chapter 9 are meant to inform a large number of behaviors around water usage.

Automation/Control: refers to whether the eco-feedback system offers or works in conjunction with a control system that can, for example, manipulate various building-related parameters to increase efficiency (*e.g.,* temperature, windows, shades).

4.4.7 Comparison

As noted earlier in this chapter, comparison is perhaps the most important part of any feedback display. Both the comparison target and the way the comparison is visualized is important. Once the first sub-dimension listed here, comparison target, is set, the remaining four sub-dimensions can be explored as applicable.

Comparison-Target: refers to *who* or *what* is used as a comparison. Targets can include self-comparison, comparison to others, and comparison to usage goals.

Comparison by Time: refers to what temporal data is used to make the comparison, such as the past week, month or same time last year. The comparison target may also be based on projected data rather than historic data, for example: "if you continue to consume at this rate, your consumption for the month will be 11% more than usual."

Social-Comparison Target: social-comparison targets are essentially drawn from one of three categories: geographically proximal groups, demographically similar groups, or selected individuals from a social network. Carefully choosing a social-comparison target is important. In Fischer's (2008) feedback review, none of the twelve studies that incorporated social normative comparisons could demonstrate an effect. She offers that, "while [normative comparisons] stimulates high users to conserve, it suggests low users that things are going not so bad and they may upgrade a little. These effects probably tend to cancel out each other." Still, social norming can be a powerful motivator. For example, Goldstein *et al.* (2008) found that hotel guests who were exposed to descriptive norms about towel reuse activity were 33% more likely to reuse their towels than a comparison group who were not. As previously mentioned, OPower has also been successful with social-comparisons and normative messages (Laskey and Kavazovic, 2011). More research is needed to understand how normative comparisons can be effectively integrated into feedback systems.

Goal-Setting Strategy: refers to the strategy used to set the goal target, which could either be self-set, system-set, or externally-set (*e.g.,* by a government or resource supplier).

Difficulty to Reach Comparison Target: The perceived difficulty in reaching the comparison target can influence a user's motivation to conserve or change their behavior (Latham and Locke, 1991).

4.4.8 Motivational/Persuasive Strategies

In this dimension, tactics or "persuasive design patterns" are used to influence the user toward action. The focus here shifts from eco-feedback that is capable of relaying types of information to a person or household about their behavior to how to *most effectively* relay that information to affect behavior. Aspects of other dimensions fall under this category as well such as Comparison, Social Aspects, and Actionability.

This dimension includes techniques described in Section 4.3 including goal-setting, commitment, rewards/punishments, competition, loss-aversion and more. However, there are far more techniques that exist than we have room to describe in this dissertation and we refer the reader to findings from fields such as persuasive design (*e.g.,* Lockton *et al.*, 2010), persuasive technology (*e.g.,* Fogg, 2002; Fogg and Eckles, 2007), behavioral science/economics (*e.g.,* Pink, 2011; Ariely, 2008; Thaler, 2008; Kahneman and Tversky, 1979), environmental psychology (*e.g.,* Ehrhardt-Martinez, 2010), game design (*e.g.,* Deterding *et al.*, 2011; Bogost, 2007), social marketing (*e.g.,* Cialdini, 2001), and health behavior change (*e.g.,* Prochaska and Velicer, 1997). See Figure 4.6 for two examples.

This dimension, perhaps more than any other, is the most underexplored and may have the most potential. However, this dimension is also potentially susceptible to abuse and most certainly involves ethical issues on behalf of the designer, about the ways in which persuasion is encoded in the display. At worst, these tactics may shift from persuasion to coercion and propaganda. That is, a designer may feel justified in making small distortions or manipulations in the data displayed in an eco-feedback system to promote proenvironmental behavior for the "common good" (*e.g.,* by providing a social-comparison target that does not exist but is portrayed as fact) but this is a slippery slope and without system transparency, a difficult one to detect. To our knowledge, a discussion of ethical frameworks within the persuasive technology space has been limited.

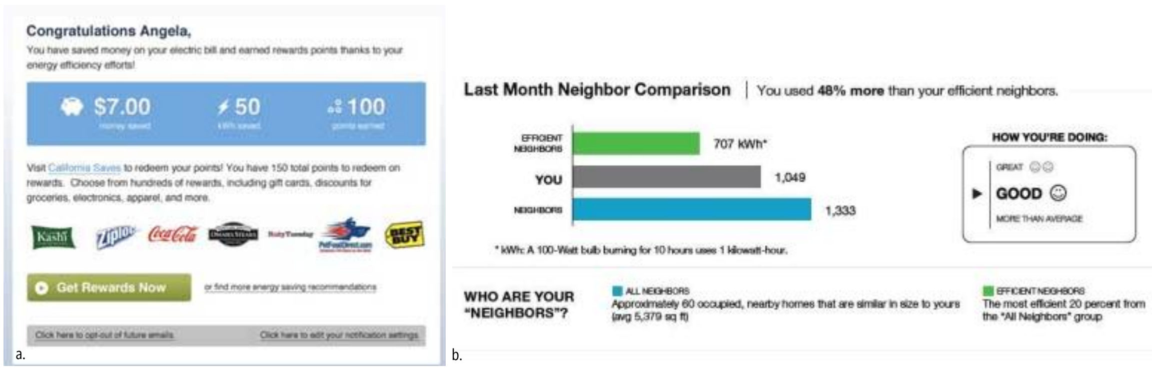


Figure 4.6: (a) Users of Efficiency 2.0[22] who reduce their electricity usage earn reward points that can be redeemed for discounts on groceries, electronics and apparel though one has to wonder if this technique simply shifts consumption (*e.g.*, to product purchases) rather than actually reducing overall environmental impact (see Berkhout *et al.*, 2000). (b) OPower uses social normative messages on their bills with social-comparison graphs to encourage conservation (Laskey and Kavazovic, 2011). The OPower bill also includes an injunctive message to indicate social approval for good behavior (*e.g.*, smiley face).

4.4.9 Other Design Considerations

Although this design space contains what we consider to be the most important design elements for eco-feedback technology, additional considerations exist, including:

- **The role of education**. Designs could incorporate educational theory.
- **The role of information vs. persuasion**. Although we touched on this point, more work is needed to fully tease out these roles.
- **Usability factors**. As with any interface, basic design elements such as button size and placement will impact the user's experience.
- **The role of ethics**. There are opportunities for manipulation or abuse with any technology aimed at modifying behavior.
- **Underlying system support for logging data useful for evaluation** (*e.g.,* number of times display interacted with, visualization most frequently selected, measurement units most frequently selected, logging of all sensed behaviors, etc.).
- **Visualization and interface support for probabilistic sensing systems** (such as the ones presented in Chapters 5, 7 and 8).
- **User trust in the information**. This can be undermined if, for example, the sensing system malfunctions or the display presents information that the user knows to be untrue.
- **Attentional requirements**. In general, eco-feedback is not sexy and not significantly engaging to most people. Consequently, users will not invest much time in trying to understand a display. Design eco-feedback systems for minutes of attention a week (or less).

[22] http://efficiency20.com/

- **Long-term changes in use**. Fitzpatrick and Smith (2009) point out three different stages of adoption and engagement in home resource eco-feedback technology: the *baseline exploration stage* where users are experimenting with the display and figuring out its use; the *awareness stage* where users assimilate to the display and use it to inform action; and *the querying and diagnosing* stage where users need more detailed analyses for one reason or another (*e.g.,* they receive a high bill) and are motivated to more deeply explore the system (Figure 4.7). The key here is to think about longitudinal use of the system and how to persistent positive change.

Baseline Exploration Stage	Awareness Stage	Querying and Diagnosing Stage
Initial period of use entails playful exploration with the feedback system and learning how to interpret it with actual usage.	After initial exploration period, users become more aware of their behaviors and routines. The display's actionability and visual efficiency becomes more important as novelty wanes.	The need to conduct more detailed analyses at ad hoc times, which may be triggered by bills, for example, as users try to determine what caused spikes in usage.

Figure 4.7: Three different stages of eco-feedback use once system has been deployed (adapted from Fitzpatrick and Smith, 2009).

- **Interplay between the feedback system and the sensing system**. One crucial aspect in guiding/constraining the design of an eco-feedback display is the underlying sensing system—they are intrinsically tied (*e.g.,* the sensing data granularity, frequency with which it is updated, and sensing location can all have significant impacts on the way the feedback system can be built). The information quality of any eco-feedback system largely rests on three components: the visual design, the underlying analytics/recommendation engine (if one exists), and the underlying sensing system that provides the former two components with data. Given this interplay, the sensing system may be considered an extension to the eco-feedback design space (*e.g.,* Figure 4.8).

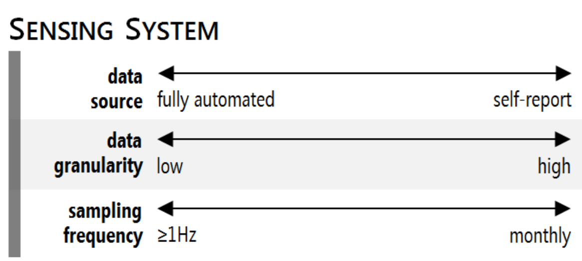


Figure 4.8: Example addition to the eco-feedback design space: the underlying sensing system.

4.4.10 Summary of Eco-Feedback Design Space

We created an eco-feedback design space to help tease out different ways of visualizing information related to behavior and the environment. In particular, our eco-feedback design space has eight dimensions based on findings from fields including information visualization, the behavioral sciences, HCI, and environmental psychology (see Sections 4.1 – 4.3 in this chapter and as well as Chapters 2 and 3). The eco-feedback design space is also useful in uncovering underserved areas of eco-feedback design and providing a structure to explore different design possibilities. Finally, but no less importantly, the eco-feedback design space introduces a vocabulary, partly borrowed from information visualization, that allows us to have a common language when we discuss, analyze, and evaluate eco-feedback designs.

4.5 CHAPTER SUMMARY

This chapter made three contributions: first, we surveyed and synthesized theoretical models of proenvironmental behavior and drew out implications for the design of eco-feedback. In particular, we argued that although no definitive model of proenvironmental behavior exists, it is critically important for eco-feedback designers to think about and reflect upon how they are imbuing models of behavior into their designs. Even if it is not explicitly recognized, all designers approach a problem with some model of human behavior. This inevitably affects the design choices that are used to create the eco-feedback system/visualizations.

While models of proenvironmental behavior provide us with a philosophical and/or theoretical basis with which to design eco-feedback systems, they do not offer specific strategies for changing behavior. Thus, our second contribution explored some of the most popular motivation and intervention techniques used in behavioral psychology, surveyed how these techniques have been applied in eco-feedback thus far, and discussed implications for future eco-feedback systems.

Finally, our third contribution synthesized the findings and related work from the above two sections as well as Chapters 2 and 3, and encoded them into an eco-feedback design space. As with any emerging discipline, frameworks help to map and crystallize the research to date and emphasize possible directions for future work. Our design space serves both as a critical lens with which to analyze existing eco-feedback systems as well as a guide to develop new ones. The design space is useful not just in the design process but in the evaluation process as well (see Chapter 9 for an application to both processes).

The end of this chapter serves as a pivot point. Chapters 5, 7, 8 and 9 describe specific sensing and feedback systems that were, in part, inspired by work from Chapters 2 through 4. In the next chapter we present UbiGreen, a sensing and feedback system to encourage green transit activities. We directly apply many of the findings from Chapters 3 and 4 and include an analysis of UbiGreen using the design space from this chapter.

Chapter 5

UbiGreen: Sensing and Feedback of Transit Activities to Support Green Transportation

Figure 5.1: The UbiGreen Transportation Display semi-automatically senses routine travel behavior such as walking, bicycling, and taking the bus and visualizes this information on the background ("wallpaper") of the mobile phone in order to promote awareness and support green transportation habits.

In the past few chapters, we have reviewed and synthesized work from a variety of disciplines that can inform the design and evaluation of eco-feedback technology. This chapter and the next four are focused specifically on integrating these findings into our own eco-feedback designs. This chapter focuses on eco-feedback for personal transportation (Figure 5.1) while the next four are focused on water.

Researchers have identified three areas responsible for a majority of energy consumption in American households: home heating and cooling; shopping and eating (and the associated transportation of goods); and commuting, flying and other daily transportation activities (Bin and Dowlatabadi, 2005; Weber and Matthews, 2008). In this chapter, we focus on the latter (personal transportation), the greatest individual contributor of CO_2 emissions (26%) in the average American household (Weber and Matthews, 2008).

Given the growing prevalence of mobile phones with sensing capabilities, one compelling opportunity to potentially impact human behavior is to offer immediate feedback about how currently sensed behaviors affect the environment. In this chapter, we explore the use of personal ambient displays on mobile phones to give users feedback about their sensed and self-reported transportation behaviors (Figure 5.1).

There is extensive literature in the areas of environmental sociology, public policy, and more recently, conservation psychology that discuss the promotion of environmentally responsible behavior (Abrahamse *et al.*, 2005; Ampt, 2003; Maibach, 2003; Vining, 2003). Past work has shown that motivators such as public commitment, frequent feedback, and personalization can positively impact environmentally responsible behavior (see Chapters 3 and 4). Since the 1990s, information campaigns and other programs have attempted to engage individuals in voluntary greening of transportation behavior (Ampt, 2003). Programs and studies have explored issues from social marketing (Maibach, 2003) to community-level interventions (Ampt, 2003). There is also literature to support the connection between increased personal awareness of everyday activity and behavior change. For example, in a review of over twenty studies exploring the effects of feedback on electricity consumption patterns in the home, the typical energy savings found were between 5 and 12% (Fischer, 2008; see Chapter 3 for a more detailed review). It is unclear, however, if feedback technology focused on transportation choices will translate into this level of reduction.

Computing technologies have begun to play a more substantial role in supporting green behaviors. A-Life Tree[23] grows on the background of the user's PC depending on CO_2 sensors in the environment; however, this is *not* tied to personal actions. The RideNow project uses a website and email to help coordinate carpooling (Wash *et al.*, 2005). Professor Tanda uses a mobile phone to teach about environmental impact in context (Chamberlain *et al.*, 2007). Other mobile applications support green transportation behaviors (*e.g.,* Carbon Diem[24] and Ecorio[25]), but little research has

[23] http://www.nyu.edu/projects/xdesign/onetrees/description/index.html
[24] http://www.carbondiem.com
[25] http://www.ecorio.org/

been conducted about how to successfully encourage green transportation choices using mobile devices.

Our work focuses on using technology to encourage green transportation habits among individuals who have a pre-existing interest in taking action to lessen their impact on the environment. Here, green transportation refers to any eco-friendly transit alternative to driving alone. We have built an application prototype for mobile phones, called the UbiGreen Transportation Display (Figure 5.1), which supports awareness of personal transportation activities, reminds users of additional reasons for being green (*e.g.,* financial savings), and reinforces their commitment to eco-friendly behavior.

We first report on two studies we performed to better understand current transportation behaviors: an online survey and an experience sampling (ESM) study (Csikszentmihalyi and Larson, 1987; Froehlich *et al.*, 2007). Both studies focused on how we might engage individuals in green behavior. Based on participants' responses to early design concepts, we determined that feedback about green behavior on a mobile device would be of value and that an iconic representation of green behavior could be engaging.

The results of these formative studies inform the design of our UbiGreen Transportation Display, an activity-based eco-feedback system for encouraging sustainable transportation behavior. This prototype uses sensors and self-report to monitor transportation activities and provides feedback on the background of the user's phone. We describe UbiGreen and then present the results of a 3-week, 13 person field study. Our results help to illustrate the value of our designs. The primary contributions of this Chapter are:

1. A working system for tracking transportation behaviors and providing feedback on a mobile ambient display;
2. A design capable of engaging users (as demonstrated by our study) with the goal of increasing their green transportation, based on a series of formative studies exploring the value of different design dimensions; and
3. A qualitative analysis of a 3-week deployment of our system, resulting in new ideas for increased social interaction, engagement and motivation.

5.1 FORMATIVE STUDIES OF TRANSPORTATION HABITS

We conducted two formative studies, an online survey and an experience sampling study, that investigated, among other things, the respondents' willingness to shift to more eco-friendly transportation, their motivations for driving, and reactions to different visual representations of transportation behavior. The experience sampling data was gathered using a combination of complementary techniques: signal-contingent sampling, diary reports and photos (Carter and Mankoff, 2005; Consolvo, *et al.*, 2007; Froehlich *et al.*, 2007). The studies supported the user-centered design process in developing UbiGreen by giving us early feedback on our visual design concepts and on the user experience of wearing and interacting with our system for tracking transportation behavior. In addition, data from the experience sampling study helped refine our transportation inference algorithms and visualization design.

5.1.1 Online Survey

The goal of the online survey was to determine people's attitudes regarding green transportation and get feedback on early visual design concepts.

Survey participants were recruited through a popular online classified ads listing service in Seattle. Respondents received a $10 gift certificate for completing the survey. Our recruitment materials stated that we were interested in "transportation practices in our community" and would be using this study "to design mobile technology to help people travel in a more environmentally-friendly way." Our goal was to reach individuals interested in using green forms of transportation, as they would be representative of the potential users of the tool we planned to build.

A total of 63 respondents (78% female) completed the online survey in July and August 2008. Respondents represented a wide range of occupations and included a flight instructor, school bus driver, students, managers, scientists, and stay at home parents. 42% of respondents lived in large cities (*i.e.,* cities of more than 500,000 people); the rest lived in towns and smaller communities.

The online survey was divided into two parts. The first section asked respondents about their transportation habits, including the frequency with which different modes of transportation were used and what influenced their choices. The second section, which could not be viewed until the first section was complete, explored design concepts for a mobile tool to encourage green transportation choices. This section explored a variety of design dimensions such as comparative versus personal data and iconic versus numeric representations.

5.1.2 Online Survey Results

The online survey helped us understand how people make transportation decisions, their willingness to engage in green travel, and their reactions to our application design concepts. We discuss each of these areas in turn.

Why respondents drive: Similar to past research (Frank *et al.*, 2007), we found a number of factors underlying a person's choice for transportation. When asked about the most important factors when selecting transport, 77% of respondents selected time to destination, 67% selected flexibility, and 47% selected cost. Combining travel with exercise was mentioned by 13% of respondents. When asked about reasons for driving by car, 45% of respondents reported that not driving would take too much time, 51% responded that public transportation was unavailable or impractical, and 57% said that they needed the car to carry things. Our results suggest that if obstacles to *not* driving could be overcome, motivations other than eco-friendliness could be used to motivate green travel.

Willingness to engage in eco-friendly travel: While only 19% of respondents reported that being environmentally-friendly was one of their top three priorities when making transportation decisions, 72% said they would be willing to set goals for themselves to travel in a more eco-friendly way. Fewer than half of the respondents (45%) thought that they were doing everything they reasonably could to travel in an eco-friendly manner. Furthermore, 61% had taken *at least one action* with the direct goal of making their transportation more eco-friendly. Popular actions included driving only when necessary, combining multiple errands into one trip, driving a hybrid or a fuel-efficient car, trying to walk more and making better use of public transportation. Of this group of respondents, 63% claimed to have maintained these eco-friendly travel choices over time.

Reactions to application design concepts: Half (52%) of respondents were interested in having feedback about eco-friendly travel on their phone, including how they did in relation to others in their city (71%). However, 54% were unwilling to share this data with others (familiar or strangers).

With regards to visual feedback preferences, respondents were almost equally divided between iconic (50%) and numeric (47%) representations. Iconic representations used an abstract image or metaphor to indicate green behavior in some way. Numeric representations used text or a bar graph. An abstract image provides less information but may add other potential benefits such as evocativeness or aesthetics, depending on its design (Consolvo *et al.*, 2008). See also Chapter 4.

These results indicate that our respondents were receptive to change and would be willing to use a system like the one that we propose in this chapter.

5.1.3 Experience Sampling Study

After the online survey, we ran an experience sampling study using mobile phones to see whether people's *in-the-moment* reasoning about their transportation choices were consistent with the results from the online survey, and to get feedback on the early designs of the transportation sensing and visual design components of our mobile application. We also used this data to help calculate how many green transportation actions people took in a week.

Figure 5.2: The MyExperience Tool (Froehlich *et al.*, 2007) was used to collect *in situ* data on transit decisions, attitudes and behaviors via context-aware experience sampling (Intille *et al.*, 2003) on the mobile phone. MyExperience would trigger a small survey like the one shown above whenever the participant was inferred to have traveled to a new location.

Seven people (five female) from the Seattle area volunteered to participate in the one-week study. Participants were recruited from among our acquaintances that were interested in green travel and were willing to work with an early prototype; six were graduate students and one was a software developer. Participants were loaned a Cingular 2125 Windows Mobile phone running the MyExperience software (Froehlich *et al.*, 2007) and also carried their personal mobile phones. MyExperience automatically triggered short self-report questionnaires on the mobile phone based on the participant's movement (*e.g.,* when a trip had completed, see Figure 5.2). These questionnaires asked about current location, the method used for transport, and, depending on the response, a series of questions about that particular transportation method. For example, if the participant had just driven somewhere alone, we asked about eco-friendly alternatives and the circumstances under which the participant would be likely to use these alternatives. We ended with exit interviews where we demonstrated our design concept and got user feedback.

Automatic trip detection was done by looking for significant changes in the visible GSM towers on the phone, which allowed us to detect trips of about half a mile or longer. Participants were asked to manually trigger a questionnaire in cases where the automatic trip detection failed and to take camera-phone pictures of anything that illustrated the experience of their daily travel (average of 14 photos per participant). This approach allowed us to test our trip detection and get situated data early in our design process with a minimum of development time, which is difficult to do in ubiquitous computing research (Carter *et al.*, 2008; Consolvo *et al.*, 2007).

5.1.4 Experience Sampling Study Results

Participants reported an average of 18 trips for the week (min: 11, max: 24). The majority of trips taken by our mobile participants were green, with walking being the most favored green transportation method. 34% of the trips were taken on foot, 26% using a bicycle, and 15% using public transportation (buses or ferry). When the participants did drive, their reasoning was similar to the reasoning provided by the survey respondents. Out of the 34 car trips total for all seven participants, they claimed that it would have taken too long not to drive for 13 of the trips (38%) and that they needed the car to carry things for 11 of the trips (32%). Also similar to our survey results, for 73% of all car trips, greener transportation options existed.

This study also helped reveal the hidden complexities behind the perception and selection of a transportation mode. One participant noted in the exit interview that when biking for transportation, he did not think of it as exercise. Reframing short trips as an opportunity for exercise could potentially make a difference in selecting vehicular travel vs. healthier (and more environmentally friendly) options. If a participant indicated in an ESM survey that s/he drove, we asked if bicycling or walking were viable alternatives. In those cases when bicycling or walking were indeed viable options, our participants reported 52% of the time that they would have been more likely to select bicycling or walking had they thought of health benefits (*e.g.,* caloric expenditure) when making the travel decision.

Finally, the participants were shown an early version of our design concept for a mobile phone application—an icon-based design representing green activity with a growing tree (similar to the tree design in Figure 5.3). All were able to understand the interface elements without prompting and were positive about having such a representation of their transportation activities on their mobile phones.

5.1.5 Design Implications of Online Survey and ESM Study

Our formative studies suggested that users could benefit from a mobile application that provides awareness of transportation routines and that they would be interested in such an application. Given the range of considerations that impact transportation choice, a design need not focus solely on emphasizing green behavior and may incorporate auxiliary benefits such as cost and health. Other factors such as stress, ability to do other things while traveling (*e.g.,* reading) may also be relevant. Prior work (Frank *et al.*, 2007) also underscores the many factors that affect transportation choice—not all of which are environmentally related. We highlight these secondary benefits in our design.

Although initially we were interested in building a social-mobile application around green transportation behaviors, our participants' ambivalence about sharing information led us to focus on a single-user application. We plan to explore multi-user applications in future research.

As users did not express a preference between the iconic representations *vs.* numeric representations of transportation behaviors in our online survey data, we decided to use iconic representations for our mobile application. Prior literature enumerates a few of the advantages of iconic visual displays: (1) they may be more aesthetically pleasing in a peripheral viewing situation (Stasko *et al.*, 2005); (2) once learned, they can easily and quickly convey glanceable information (Matthews, 2007); and (3) they may evoke other responses such as emotional attachment (Dillahunt *et al.*, 2008; Donath, 2004). However, iconic representations often do not offer the same level of detail as their numeric counterparts.

5.2 UBIGREEN MOBILE APPLICATION

Based on the results of our formative work, we created the UbiGreen Transportation Display, a mobile phone-based application that provides personal awareness about green transportation behaviors through iconic feedback. Small graphical rewards are earned by taking "green" transportation such as riding the bus or train, walking, biking, or carpooling. Although each of these activities has different CO_2 emissions, we counted them equally, as each is preferable to driving alone. Once a green transit activity is sensed, the background (wallpaper) of the user's phone is updated accordingly. A phone's wallpaper represents a critical area of screen real estate as it is seen nearly every time the device is picked up and used. In this way, the wallpaper functions as a type of personal ambient display (Consolvo *et al.*, 2008; Matthews, 2007).

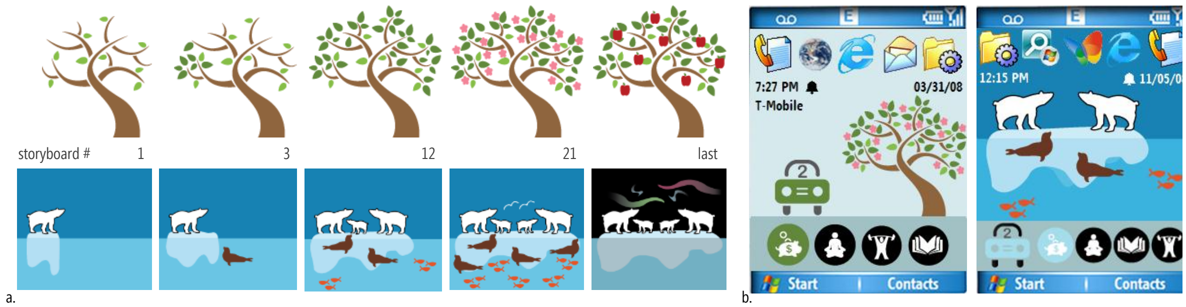


Figure 5.3: (a) The tree and polar bear storyboard progressions. (b) One of the tree and polar bear storyboards shown in context on the background of the mobile phone. In both cases, the current activity is carpooling indicated by a car icon with the "2" in the windshield. Since carpooling saves money, the piggy-bank icon is also highlighted in the secondary value icon bar.

Our designs are partly based on a finding from social psychology that cognitive representations of different concepts become linked if those concepts are repeatedly encountered together (Higgins, 1996). We take advantage of this fact by jointly presenting a representation of eco-friendly transportation and representations of other goals—such as saving money, getting exercise, etc.—that the user may care about. The interface emphasizes these sub-goals automatically when green transportation is taken.

We were also influenced by research in conservation psychology that showed how caring for animals helps humans connect with nature (Myers and Saunders, 2002). Dillahunt *et al.* (2008) adapted this notion and explored how "virtual polar bears" could be used to motivate green behaviors. They found that emotional attachment to a virtual polar bear could translate into concern for the environment and a tendency towards taking green action. This research paired with the results of our own formative work lead us to create two different iconic representations to reward green behavior (Figure 5.3).

5.2.1 Visual Designs

In one interface, a tree is used to indicate green transportation activity. At the start of each week, the tree is almost bare. Leaves, blossoms, and eventually apples are progressively added to the tree after each green transportation event. In the other interface, a polar bear is shown on a small iceberg. Over the week, the iceberg grows as green transportation actions are taken and the surrounding ecosystem also improves. For example, new food sources such as fish and seals appear (Image #12 in Figure 5.3). Both designs follow a linear sequence of images. The last image in the sequence provides a small, but engaging final reward. In the tree design, the flowers give way to fruit and in the polar bear design, the sun sets and the Aurora Borealis (Northern Lights) appears. The images never return to a previous state due to inactivity, but at the start of each week, the interface is reset to the first image in the sequence. The entire background area of the screen is filled although small parts of the images are obstructed by menus and text (right-side images in Figure 5.3). Due to technical limitations on Windows Mobile devices, the image transitions were not animated.

In both designs, an icon representing the most recently sensed green transportation activity is shown (*e.g.,* in the right two designs of Figure 5.3, the most recent activity is a “carpool”). In addition, at the bottom of the interface, four icons are shown representing other potential benefits of this activity: a piggy bank represents money savings, a person meditating represents relaxation, a weightlifter represents exercise and a book represents the opportunity to read or do work, for example (see also Figure 5.6). These four icons were chosen based on the results of our online survey, which indicated that financial savings, exercise, opportunity to do other things while traveling, and “time to think” were reasons for taking green transportation. Although one could reward users differently depending on the carbon footprint of their current transit activity we chose not to do so for simplicity (*e.g.,* walking produces zero carbon vs. carpooling, whose per person carbon footprint is dependent on the car type, number of passengers, distance traveled, etc.).

5.2.1.1 Analyzing the UbiGreen Visual Design through the Eco-Feedback Design Space Lens

We can use the eco-feedback design space presented in Chapter 4 to analyze critical elements of the design; see Figure 5.4.

Information Access: Perhaps most importantly, the *accessibility of the information* is extremely high—by using the background of the mobile phone (a device that most of us carry everywhere), the transit feedback data is nearly always present at hand and the effort to access the feedback is low. UbiGreen updates in real-time and offers feedback co-located with the target behavior (transit).

Data Representation: Second, in terms of *data representation*, UbiGreen is more artistic than pragmatic but uses iconography in a way that allows the user to track progress throughout the week. The primary visual encoding is graphical (there was no text), relatively simple visual complexity; however, the as an artistic display, the information was not immediately understandable without explanation or direct use. The measurement unit was number of green transit activities instead of, for example, amount of carbon emissions or miles traveled.

Interactivity: Ideally, the system would have required no direct user interaction other than a glance at the data; however, due to transit sensing and inference limitations, we relied on the user to self-

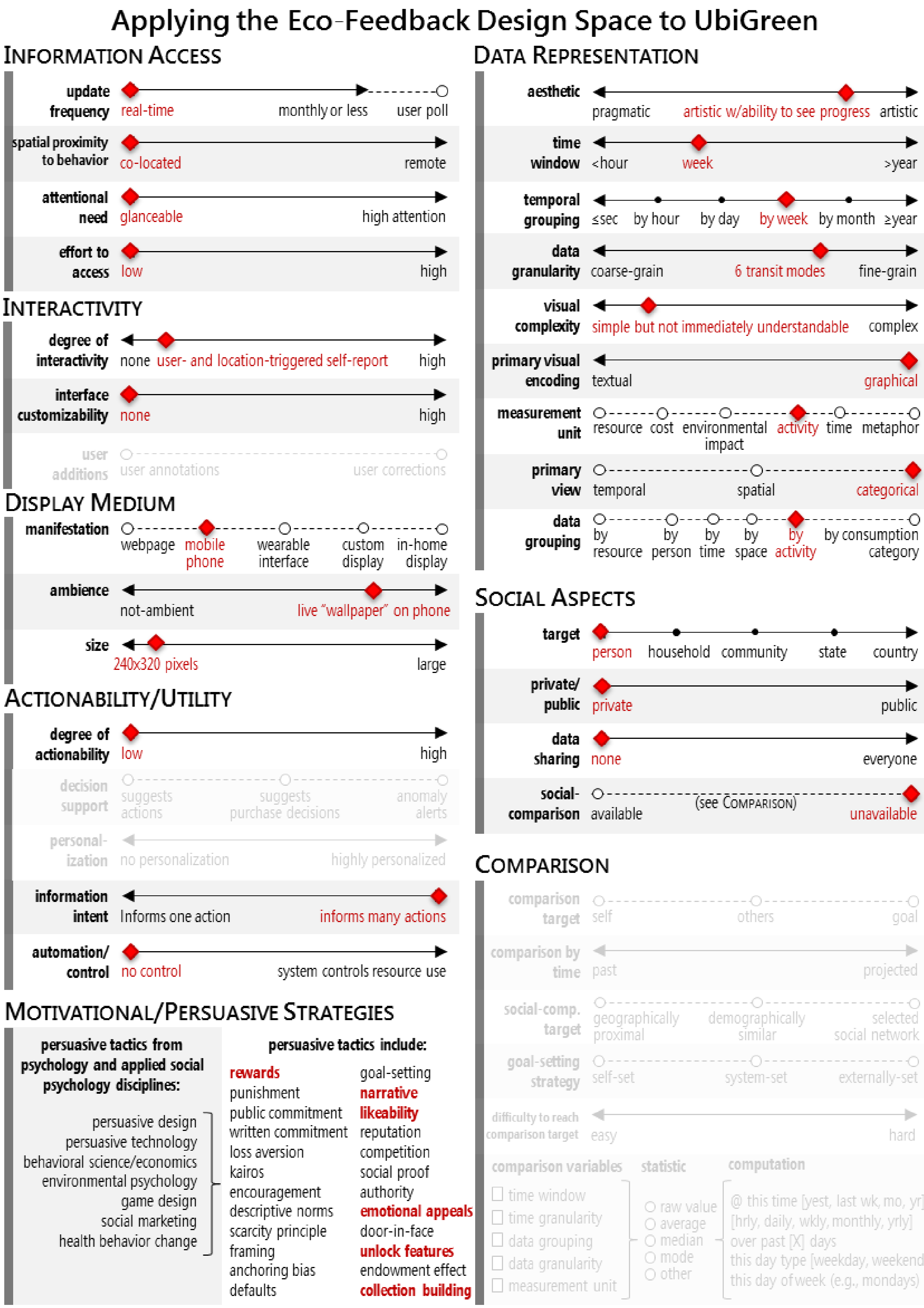


Figure 5.4: Applying the eco-feedback design space from Chapter 4 to the design of UbiGreen.

report certain transit activities (such as driving in a car alone vs. carpooling). The interface was not customizable (*e.g.,* users could not choose their own storyboards).

Display medium: As previously noted, the UbiGreen display ran on the background of the user's mobile phone on a 240x320 pixel screen. The interface was designed to be ambient and glanceable—in the sense that the user could see the information as a side-effect of pulling out and using their phone.

Actionability/Utility: UbiGreen had a low degree of actionability in that it does not explicitly provide information to the user on *how* they can best change their behaviors to reduce their carbon emissions or even suggestions for alternative transit based on sensed travel routines. The *information intent* was to inform multiple actions—*i.e.,* different types of transit modes and routines.

Social Aspects: UbiGreen was designed for individuals and did not support data sharing (though, as you will see in our results, many participants physically showed off their display to others). In addition, as an eco-feedback display running on the mobile phone, it was designed for personal rather than public use.

Comparison: UbiGreen did not explicitly support comparison of any sort (not self-, social-, or goal-comparisons). As the display reset on each Sunday, the user would have to remember the green transit feedback stage reached from the previously week to compare week-to-week performance.

Motivational/Persuasive Strategies. Many of our design elements were influenced from the motivation techniques section of Chapter 4 as well as the game design literature. For example, the visual adaptations that would occur after green transit was sensed could be perceived as rewards. The storyboards themselves were game-like narratives where the user's actions in the real-world affected how the story progressed. Both the tree design and the polar bear design portrayed a sense of "stages" and "unlocking features" by adding new elements that were not previously available once a number of green trips were completed (*e.g.,* the tree stages went from bear tree, to leaves, to flowers, and finally, the last stage, fruit).

In summary, the eco-feedback design space is useful to better understand how a feedback system is designed but also to uncover open areas for improvement. In this case, the limited actionability and comparison aspects of the display could be improved in future designs.

5.2.2 Implementation

The UbiGreen prototype was built in C# using .NET CF along with two open source tools: MyExperience (Froehlich *et al.*, 2007) and ActivityDesigner (Li and Landay, 2008). UbiGreen relied on three sources for transportation data: a Mobile Sensing Platform (MSP) (Choudhury *et al.*, 2008), the phone's own GSM cell signals, and the participants themselves. The MSP sensor, shown in Figure 5.1, is a small device about the size of a pedometer worn around the belt and contains ten sensors including a 3-axis accelerometer, a barometer, and infrared light sensor. Its onboard algorithms are able to accurately differentiate sitting, standing, walking, running and cycling activities. To avoid recording erroneously detected activities, participants did not receive credit for automatically sensed transit activities that were six minutes or less in duration.

We used GSM cell tower information similar to Sohn *et al.* (2006) to infer when a participant was traveling by vehicle (car, bus, or train). In particular, we used a sliding window algorithm to continuously calculate the rate-of-change between the strongest visible seven cell towers. We *could not* automatically distinguish between these transit modes. Consequently, in these cases, UbiGreen would trigger a two question self-report questionnaire (a "travel survey") on the mobile phone asking about the exact form of travel (*e.g.,* bus, drove alone, or carpooled; see Figure 5.5c). This questionnaire was only triggered after we inferred that the transportation had ceased to avoid the possibility of creating driving distractions. If the automated sensing methods failed to detect a trip, the participants could still get credit for a green transportation activity by invoking a transit survey themselves. To avoid redundancies in the data, both the manually triggered and the motion-triggered self-report surveys were prefaced by a dialog informing the user about their most recently recorded transportation activity (Figure 5.5b).

UbiGreen was built, in part, using ActivityDesigner, which allows designers to rapidly create applications that react to data about human activities (Li and Landay, 2008). ActivityDesigner uses a combination of storyboarding and demonstration to create application behaviors. UbiGreen reported transportation activities over the Internet to ActivityDesigner, which would then calculate the next image to be displayed and send that image back to the phone. ActivityDesigner also provides an interface to playback collected field data. This allowed us to replay events sent from our participants' phones during the field study. This was useful in debugging early versions of the prototype as well as helping to monitor our participants' data as it was being generated (Figure 5.7).

The UbiGreen prototype also included an "information" screen that provided feedback about the real-time activity inference, the status of the Bluetooth connection to the MSP, and information about the user's mobile Internet connection (Figure 5.5a). During the first week of our field study (see below), participants had expressed disappointment when the sensing technology did not sense all of their trip activity or did not sense it accurately enough to earn credit. We quickly added the new information screen, which allowed participants to more easily detect whether their hardware was working and whether their current transit activity was automatically being sensed.

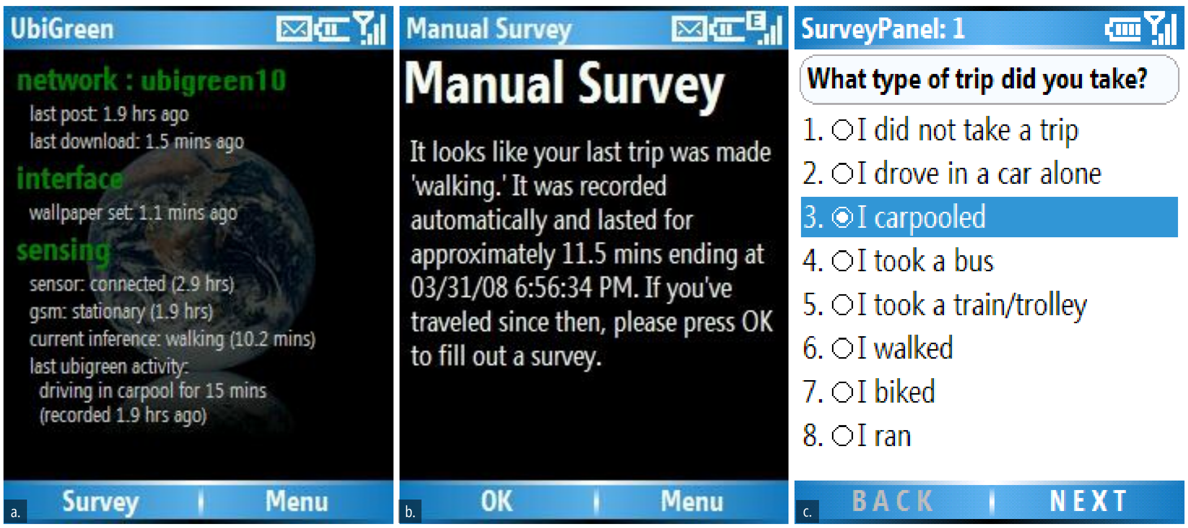


Figure 5.5: Non-wallpaper UbiGreen screens: (a) UbiGreen's application screen where the user could choose to launch a self-report survey and see status information from the sensing and inference system. (b) The manual survey screen. Note that it explains to the user about the last recorded activity to ensure that duplicate activities were not recorded. (c) The first survey screen asks "What type of trip did you take?"

5.3 UBIGREEN FIELD STUDY

We used a combination of rapid iteration and field testing to get *in situ* data on the use of UbiGreen. Our goal was to compare the two visual designs and to explore issues such as social use, the most engaging aspects of our design, and responses to the changing iconic progress representations. We were also interested in exploring the viability of using semi-automatic sensing for recording transit activities.

Before we give the details of our study and results, it is important to comment on our methodology and the resulting timeline. The ability to get *in situ* data at early stages of application development is an acknowledged problem in the literature (Carter *et al.*, 2008; Consolvo *et al.*, 2007), and many researchers have engaged in tool and technique development to address these issues (Carter *et al.*, 2007; Froehlich *et al.*, 2007; Li and Landay, 2008). Because this was a design exploration, we heavily leveraged rapid development tools such as MyExperience (Froehlich *et al.*, 2007) and

ActivityDesigner (Li and Landay, 2008) that allowed us to test our application *in situ* within only a few months of the start of our software development process.

Figure 5.6: When walking is sensed, the UbiGreen background display would change to look like it does in this figure. Note how the secondary value icon bar highlights the "saving money" and "exercise" icons, which serve to reinforce the benefits of walking.

That said, UbiGreen is a sophisticated technological artifact relying on external hardware sensors, mobile phone Internet connectivity, real-time inference algorithms, and backend server calculations to produce the desired application behavior. As a result of this complexity, the technology did not always function optimally during the course of the study. Some participants, for example, had trouble maintaining a stable Bluetooth connection between their mobile phone and the MSP. Others found the MSP cumbersome to wear (particularly women who did not always have a belt or belt loop for attachment). Next, we provide more details about our participants and method.

5.3.1 Participants and Method

Participants were recruited from two major metropolitan cities, Seattle and Pittsburgh, to increase the diversity of perspectives in our resulting data. We evaluated participants' level of environmental concern using De Young's (2000) scale of 1 to 5. Our Pittsburgh participants were significantly less concerned about the environment (M=2.95, SD=0.19) than our Seattle participants (M=3.72

SD=0.22, $F_{1,14}$=7.0, p<.05). Recruitment was done by posting to the Pittsburgh and Seattle Craigslists and using a CMU's online recruitment service. The ads stated that we were "investigating how mobile phones could be used to encourage sustainable transportation choices." We selected participants who had AT&T or T-Mobile mobile phone service plans, as UbiGreen required GSM cell network operators for its motion inference. Participants were paid $100-$300 depending on the length of their participation in the study.

Participant ID	Location	Condition	Days	Occupation
P1	Pittsburgh	Tree	27	Sales Clerk
***P2**	Pittsburgh	Tree	N/A	Attorney
P3	Pittsburgh	Tree	21	Law Enforcement
P4	Pittsburgh	Tree	9	Student
P5	Pittsburgh	Polar Bear	20	Technical/Engineering
P6	Pittsburgh	Polar Bear	12	Student
P7	Pittsburgh	Polar Bear	16	Student
P8	Seattle	Polar Bear	6	Student
P9	Seattle	Tree	42	Office Admin
P10	Seattle	Tree	19	Consultant
P11	Seattle	Tree	25	Program Manager
P13	Seattle	Polar Bear	37	Programmer
P14	Seattle	Polar Bear	30	Consultant
P15	Seattle	Polar Bear	6	Student

Table 5.1: Participants involved in UbiGreen field study. Of the 14 participants, 7 saw the tree graphics and 7 saw the polar bear graphics. Duration ranged from 1 week to 4 weeks. *P2 dropped out of the study. Her data is not included in our analysis

Out of the 14 participants, 6 were from Seattle and 8 were from Pittsburgh (Table 5.1). The majority of participants were drawn from the working populations of both cities, although 5 were students (1 undergraduate). Half were male and half female, the average age was 26-30, and the study included two couples. Participation lasted from 1 to 4 weeks (average of 21 days, median=20).

At the beginning of the study, participants were supplied with a Cingular 2125 phone running the UbiGreen prototype, which was intended to replace their current mobile phone (we moved their SIM card for them). They also received a pager-sized MSP sensor. One participant (P2) found that the Cingular 2125 phone was incompatible with her work and thus had to drop out of the study. The participants were given an explanation of the UbiGreen prototype and training on their new phone. We also provided a 24 page manual and three one-page quick reference guides documenting how to use the Cingular 2125 mobile phone, the MSP, and the UbiGreen application.

We randomly assigned seven participants the polar bear visuals and seven participants the tree visuals, balanced across conditions. At the start and end of the study, participants were asked to complete a questionnaire that included relevant questions from our earlier transportation study, demographics and environmental attitudes. We also interviewed participants about their experience with the application at the end of the study.

During the field deployment, a number of strategies were used to ensure that the UbiGreen sensing and feedback system was functioning properly. First, UbiGreen would automatically notify the participant if the MSP device was malfunctioning or if it seemed that the participant forgot to wear the device. Second, the research team could view a secure website of each participant's current UbiGreen background display (Figure 5.7). Finally, UbiGreen also sent text messages to the research team when certain irregularities were detected (*e.g.,* system crashes or phone restarts).

Figure 5.7: The research team could view the above website to track the status of our participants in real-time. This website was not publically accessible and not available to the participants themselves. Note the differences in different stages achieved in the storyboards between the Monday view (a) and the Saturday view (b).

5.4 RESULTS OF THE UBIGREEN FIELD STUDY

The goal of early-stage *in situ* deployment is to show that an application concept is feasible and to learn how it may be used and how this differs from the expectations of the researchers. We analyze our interview and transit data with respect to four issues that relate to feasibility and use: (1) the viability of using automatic sensing to detect transportation patterns; (2) qualities of our two visual designs; (3) opportunities for engagement with the issue of sustainable transportation; (4) and finally, the potential to influence behavior change.

5.4.1 An Overview of the Data

Our exit interview used an open-ended, semi-structured format and asked participants to describe their experiences using UbiGreen. Our transit data was logged via automatic sensing and self-report. We collected an average of 21 days of data per participant (16 days in Pittsburgh and 27 in Seattle). A "day of participation" was only counted as such if we logged at least one sensor event for that day. This was to ensure that our daily averages were not underreported. A total of over 8.4 million sensor events were logged during the study. Sensor events included GSM cell information, device usage (SMS, Internet browsing activity, phone call activity), and UbiGreen related activity data.

Transit Activity: Of the 8.4 million logged sensor events, 1,129 were travel events, 872 (77%) of which were green. This is 4.2 transportation events per day on average across participants (3.2 of which were green). The average trip length was 18 minutes (23 minutes for green trips). The number of total trips per day is in line with previous research on daily transportation behavior (Froehlich and Krumm, 2008; Hu and Reuscher, 2004) which provides evidence that we were accurately recording transportation behaviors. Figure 5.8 presents the statistical breakdown of observed transit activities in our dataset. Like in our ESM study, the most popular form of transportation overall was "walking" accounting for 31% of the recorded trips (average length 13 minutes). The second most popular form of travel was "driving alone" (22%, 13 minutes), followed by "carpools" (19%, 19 minutes) and "bus rides" (19%, 22 minutes). In Pittsburgh, carpooling (31%) and walking (31%) were the top two most popular forms of green transportation, whereas in Seattle walking (32%) and riding the bus (20%) were the two most popular.

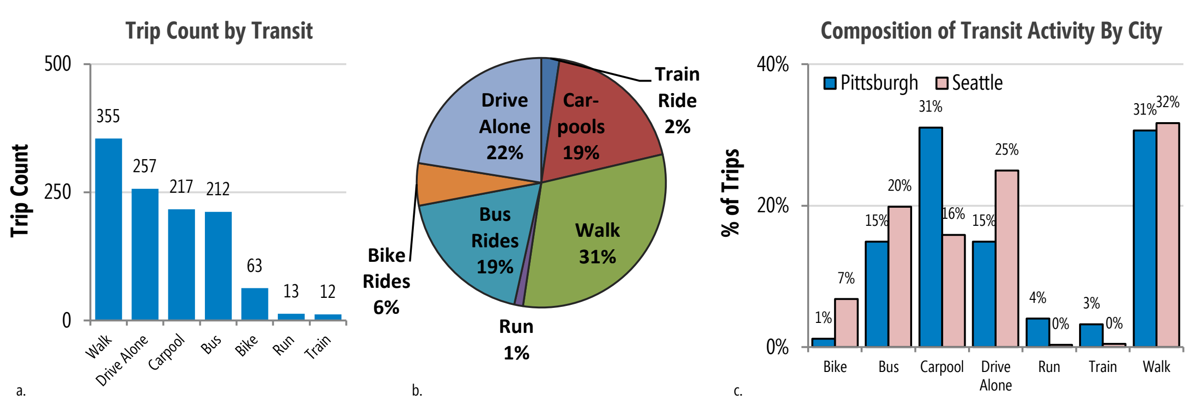


Figure 5.8: (a) The raw number of trips broken down by transit mode. (b) The percentage composition of all recorded transit activities. (c) The percentage breakdown of transit activities by city.

Data Acquisition: Transit data came from three sources: the MSP, GSM-based motion inference (which triggered a survey asking what type of vehicle the user was in), and the participant him/herself. The MSP accounted for 24% of the recorded trips (Figure 5.9). GSM-triggered surveys accounted for 35% of our data and manually invoked surveys accounted for the rest (41%). In all, 856 surveys were completed with a median completion time of 18 seconds.

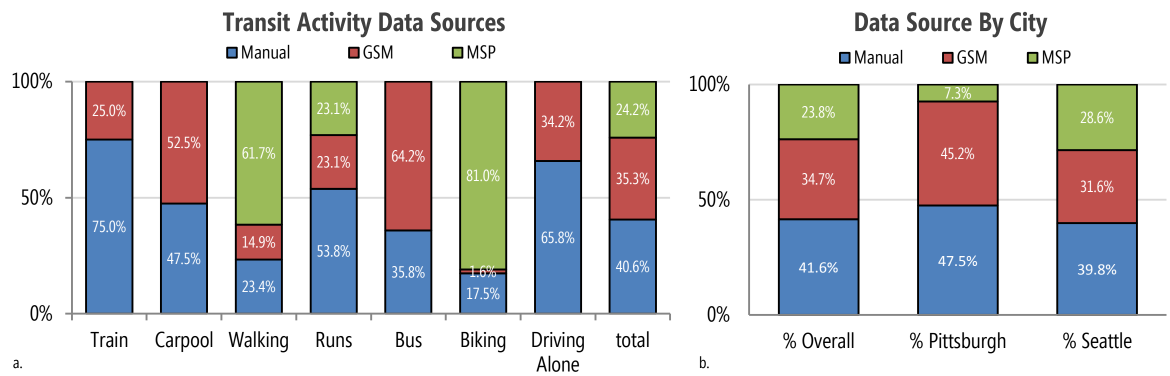


Figure 5.9: The source of UbiGreen transit activity data broken down by (a) transit activity and (b) city.

5.4.2 Viability of Automatically Sensing Transit Activities

As one participant observed, UbiGreen's full potential rests upon its ability to automatically sense transportation activity, "everything should be automatically detected" (P7). Although this is technically challenging, our early prototype performed quite well at automatically sensing walking and bicycling and our GSM motion algorithms accounted for a majority of bus and carpool events.

Still, we were hoping that the number of manually invoked surveys would be lower. One reason that they were not, we believe, is because our vehicle trip detection had a delay between the end of a trip and *inferring* that the trip had indeed ended ("I did get travel surveys after I took the bus. Sometimes it took way too long though and I would trigger the survey myself" (P13)). From interviews, most participants found that the sensing worked quite well: "The car detection was very good. Within 1 or 2 minutes after the activity was complete [I would get surveyed]" (P7).

Requiring our participants to wear an additional sensor (the MSP) was an obvious burden, "I guess the biggest annoyance for me was just having an extra piece of gear to wear" (P11). We have recently developed activity inference algorithms for the Apple iPhone using the built-in accelerometer and Nike+iPod piezoelectric shoe sensor capable of detecting walking, running, and bicycling in a laboratory setting with 98% accuracy (Saponas *et al.*, 2008).

In summary, sensing was viable but could be further automated. In addition to our iPhone inference work, we have also investigated how GPS signals can be used to discriminate between train, bus, and driving activities (much work has been published in this area as well since our UbiGreen work was performed; see Chapter 2).

5.4.3 Visual Design Qualities

Participants commented that the presence of the visual display on the background screen of the phone increased personal awareness and stimulated reflection about their transportation activities. "It really encourages you to analyze your own performance" (P8). As observed in previous studies (Consolvo *et al.*, 2008), the wallpaper is frequently visible to participants as they go about their normal phone usage. One participant said, "it's omnipresent" (P9). Participants also seemed to appreciate that their "green" transportation led to a progression of the visual design shown on the phone screen. "I liked the tree because it was, to my mind, a pretty progress bar. There was enough of a clear distance between each state that I could tell the difference at a glance" (P11).

Some participants wanted more variety in the visual rewards. "The first couple of times were interesting [when the background changed]… but then it started repeating" (P13). Participants P8 and P11 both thought we could "have different stories every week … to maintain curiosity in the app," (P8) and that we, or others, could "generate their themes online and share them" (P11). Future designs could also follow non-linear storytelling patterns where users follow certain thematic arcs based on their performance (similar to a choose-your-own adventure style book, only the branching through the story is chosen automatically based on transportation behavior).

Iconic vs. Numeric Representations: Participant feedback indicated an interest in knowing *actual* carbon emissions in addition to seeing the iconic progression of the arctic ecosystem. "I would like more information about carbon emission savings" (P15). Tracking carbon savings, however, is quite challenging with current technology. As P11 noted, "if you tracked all carbon emissions or gallons saved it would be based on what kind of bus you rode in and what kind of cars people drove, it would get really complicated." Despite these challenges, it is possible to calculate an approximate impact that gives participants a sense of progress. We will explore this in our future work.

Secondary Icons: Most participants noticed the secondary icons at the bottom of the interface but few were impacted by them. "I didn't feel like they added a lot of information, like I know biking is a good form of exercise" (P11). Another participant pointed out that the secondary icons would be more interesting if "the circles filled up as you did more of those activities [over time]" (P10). We believe that highlighting secondary benefits for green transportation is still a promising area for future work, particularly when those benefits are highly personalized and highlighted in the moment (*e.g.,* by informing them that a bus route is actually faster than driving or that bicycling to work would save X dollars over the month).

Negative Imagery: Some participants were keen to mention using both positive and negative imagery depending on performance, “I think negative reinforcement would also be good. I think maybe my polar bear should drown if I am bad” (P14). Another participant was even more macabre. He stated that if you were really bad, “maybe penguins should show floating dead-up in the water.” (P15). It may be worth pursuing future designs that include both positive and negative reinforcement—leaves falling from the tree, for example, when a user drives excessively. These options could then be evaluated more systematically for impact.

In summary, our visual design was effective and *present*, but participants asked us to show more detailed information (such as more varied stories; actual carbon savings; tracking secondary benefits numerically; and so on).

5.4.4 Opportunities for Engagement

Although in a field study of this length, novelty likely plays a strong role in application usage levels, it is still interesting to highlight aspects of our design that participants specifically mentioned as motivating. Two unexpected themes arose—one was the idea of the application as a real-life game and the other was the anticipation and curiosity inherent in moving through the sequence of images.

UbiGreen as a real-life game: Although we did not describe UbiGreen as a game to our participants, many perceived it as one. In interviews and in our freeform post-study survey data, participants would use game-like metaphors when describing the application. For example, participants mentioned that engaging in green transit behaviors earned “points” and making it to the last screen was the “final level.” One participant even complained that when a trip hadn’t been automatically recorded, “I felt like I was being cheated out of my points” (P15).

Because so many participants conceptualized UbiGreen as a game, they considered opportunities to “cheat” the system to be problems. One participant described UbiGreen’s method of “earning points” as potentially flawed, “I don’t like incentives for getting points artificially by taking unnecessary trips… like trying to beat your own score by taking two more trips just to earn points.”

(P11). This participant was worried that UbiGreen might encourage people to take *more* trips simply to earn more points (some green trips could lead to more emissions than no trip at all).

Future designs that incorporate a more overt gaming model could mitigate these effects by rewarding "more points" for zero-carbon trips such as bicycling and walking. The application could also reward the user for taking fewer trips from week to week. Finally, although carbon tracking is still an active form of research (Weber and Matthews, 2008), a progress bar (or some other visual indicator) could be used to reveal total carbon emissions for the week.

Anticipation and Curiosity: We did not disclose the image sequence or "final image" to participants ahead of time. This created a sense of anticipation and curiosity. P10 commented "I liked that we didn't know what it was going to do. Like when your phone turned from leaves into flowers and then apples." Similarly, P14 said "I wasn't sure if there was anything else [after the Northern Lights], so I kept going." As previously mentioned, designers could take advantage of this by offering new weekly themes or themes that continue progressing through a story over time.

Social Sharing of Transportation Activity: Although our design was not inherently social, nearly all of our participants commented that the graphics on their phone's background display became conversation starters at work and at home. More interestingly, however, some co-workers seemed to take an interest in participants' progress "Some people at work knew about the polar bear and every day they asked me about it. 'Did you get a seal today?'" (P14). Similarly, both of the couples that participated in the study developed a sense of competition. "There was a competition with P15 like I mentioned; he would always ask about my phone" (P14). "Yah, P14 started a day before me so that I was always one day behind her" (P15). We believe that exploring how social motivators like competition can be used to influence transportation behaviors is a rich, open area of future research (Petersen, 2005).

Real Time Recommendations: In the UbiGreen field study exit survey, we asked participants what could help them to make more green trips. The top two things they selected were reliable transportation (79%) and financial incentives (71%). However, more knowledge about alternatives (56%) also received a high rating. Specifically, P13 mentioned that one improvement to UbiGreen could be a recommendation system that suggests alternative forms of transportation based on your personal trip history. In cities like Seattle, where the public transit system publishes real time data about bus locations using GPS, these recommendations could be very specific. Such a system could even incorporate shared commute data by other UbiGreen users—“42% of the people who live in your neighborhood and work in Capitol Hill take the bus.”

In summary, users encouraged us to do more with the game-like properties of UbiGreen and to factor in real time data about friends and/or transportation options, time, cost and CO_2 savings. This would also address the issues of convenience raised in our online survey. In some cases, it may be that a green form of transit is actually faster than driving (*e.g.,* buses can circumvent traffic by using the high-occupancy vehicle lanes).

5.4.5 Potential for Behavior Change

Our formative work showed that participants would value feedback about their transportation choices and identified forms of feedback that might help to support and sustain greener transportation choices. Our field study clearly demonstrated the viability of our concept, to which participants responded positively on many fronts described above. In fact, 7 of the 13 participants continued using the software beyond the planned end of the study. Participants talked about gaming and points, and expressed concern about cheating, all indications that they were engaged by the system. While an early-stage study like this cannot reasonably be expected to *confirm* that behavior change occurred, our qualitative results indicate that participants were engaged in the application (a prerequisite for behavior change) and did start new behaviors.

At the end of the study we asked whether participants felt that UbiGreen had encouraged them to travel in a more eco-friendly way and what they did this week to be more green. In open ended responses on our exit questionnaire, three participants gave specific answers about changes they had made. P3 wrote “I’ve been carpooling to work and walking to my familys [sic] houses because they are close enough to do so, though before i [sic] would usually just hop in my car.” P9: “I’ve tried to carpool more to go to church (I go to church more than once a week).” P10 reported “…learning to ride a bicycle more confidently.” Two of these (P3 and P9) were the least green participants involved in our study. Most other participants told us things like “I feel I already travel in a relatively eco-friendly way and the study did not change that” (P15), a reflection of the fact that most of our participants were already very green and had lifestyles amenable to not driving (such as living and working in an urban area or living next to a bus stop). A common request amongst our participants was the ability to compare their current week’s performance with previous weeks. This also implies an interest in understanding how their own behavior changes over time.

Still, some participants felt that the visual feedback was not enough to change their transportation habits. For example, P6 mentioned that “It definitely keeps you more aware of it [transportation habits] every single day. You use your phone every single day so you know… but I’m not sure if being aware of it changes your habits.” Only a longer and more controlled study can truly answer this question.

5.5 CHAPTER SUMMARY

In this chapter, we presented results from a set of formative studies exploring individual transportation, which led to the development of the UbiGreen Transportation Display, a mobile application prototype that semi-automatically senses and reveals information about transportation behavior. We described the results of a 3-week field study of the use of our prototype in two distinct U.S. cities. Our contributions from this research are a system that semi-automatically tracks transportation behaviors, a visual design capable of engaging users in the goal of increasing green transportation, and implications for the design of future green applications. The results and experiences derived from this field deployment factored directly into the refinement of the eco-feedback design space in Chapter 4. They also helped inform our water usage eco-feedback explorations, which are described in detail in Chapter 9. The next chapter serves as a transition point from personal transportation to the water portion of the dissertation.

Chapter 6

Investigating Water Use in the Home

"When the well is dry, we know the worth of water"

—Benjamin Franklin, 1746

In this chapter, we transition from personal transportation to water use. As motivated by Chapters 1 and 2, many cities around the world are facing an escalating demand for potable water due to increasing populations and a shift in population density from rural to urban areas (Willis *et al.*, 2010; Barlow, 2007). To reduce residential water consumption, the water industry has largely focused on regulatory and financial incentives. However, these approaches often do not address a fundamental problem: most home occupants have little-to-no knowledge about water usage in the home and limited means to find out.

This lack of awareness and understanding about water leads to inefficient practices such as irrigating during mid-day or using the full-load cycle on a laundry machine when washing only a few clothes. And, because so few people have a strong understanding of water usage amounts, they have difficulty determining anomalous or excessive usage on their water bills (unless these excesses reach extraordinary amounts). In addition, past studies have shown that the fifth most water consuming source in the home is actually from *leaks*, accounting for 13.7% of residential use (Mayer *et al.*, 1999)—much of this is from leaky toilets (EPA, 2008). Yet, even these cases of unnecessary waste are difficult to identify and solve with current water sensing and feedback systems.

Although energy usage has received a great deal of attention in HCI research (as discussed in Chapters 2-4), the needs, concerns, misconceptions and motivations surrounding water use may be different and therefore may require different forms of eco-feedback. For example, unlike electricity where heavy energy use tends to be from automated sources (*e.g.,* central air conditioning systems, refrigerators, and electric heating), heavy water use often involves some sort of manual human behavior (*e.g.,* showering, toilet flushing, doing the laundry, and lawn and garden watering). In addition, in contrast to electricity where there are a number of commercial products that motivated customers can purchase to get feedback on their electricity usage (*e.g.,* The Energy Detective (TED)[26], Blueline Innovations Power Cost Monitor[27], or P3's Kill-A-Watt[28]), water has no such products. Thus, the bill most often remains a household's only feedback point on water consumption. Finally, the cost of water is often much cheaper than the cost of electricity, which gives rise to questions about motives for conservation.

To inform the design of eco-feedback displays for water consumption, we conducted a formative study examining perspectives of water and water usage practices in the home. In particular, we performed an online survey of 656 respondents from around the United States and Canada, focused on exploring knowledge of water consumption for everyday activities like showering and toilet usage, knowledge of water cost, desire to conserve water, concerns around water supply and sewage, and motivations for conserving water (*e.g.,* environmental vs. financial). Several findings provide direct implications for the design of eco-feedback displays for water consumption. For example, most respondents were relatively unaware of their water consumption habits and had misconceptions about where water comes from, where it goes, and how much is used for daily activities. We used the data, in part, to inform the design of our own novel water usage feedback displays, which are presented and evaluated in Chapter 9.

In this chapter, we first discuss the factors influencing water consumption from the environmental psychology, sociology and water research fields. We then present the survey method and results, and discuss implications for the design of eco-feedback displays for water.

[26] http://www.theenergydetective.com/
[27] http://www.bluelineinnovations.com/
[28] http://www.p3international.com/products/special/P4400/P4400-CE.html

6.1 BACKGROUND: FACTORS INFLUENCING RESIDENTIAL WATER USE

Although a number of HCI researchers have designed and, in one form or another, evaluated eco-feedback displays for water (see Chapter 2), few studies have looked at or incorporated past research into water attitudes, practices and history. Such background is relevant because it provides additional perspectives with which to shape and focus the eco-feedback water research agenda. Indeed, it expands water eco-feedback to consider not just individual choices around consumption but the larger infrastructural, cultural and social components under which those choices are made.

Water research scientists and managers have identified a number of factors that correlate with water usage. These can be broken down roughly into six groups (1) *background demographic variables* such as family income, education level, retirement status, number of people in the household, number of children, number of people with fulltime jobs, and socioeconomic status; (2) *house variables* such as house age, house value, number of water-using appliances, number of bathrooms; (3) *attitudes, beliefs, and motivations* concerning water usage and the need for conservation; (4) *understanding and awareness of specific water usage strategies* intended to reduce water use including installing water-saving fixtures and appliances, curtailing outdoor water use, and changing behavior to reduce indoor use; (5) *temporal context* such as season and time of day; and (6) *regional and national* regulatory structures and management efforts. This list is synthesized from Hamilton (1983), Cooley *et al.* (2007), Memon and Butler (2006), Vickers (2001), Jeffrey and Geary (2006), Fox *et al.*, (2009) and Kenney *et al.*, (2008).

Whereas the Background and Related Work chapter (Chapter 2) explored some of these factors—particularly the effect of regulatory structures and demand management efforts on water use—this section focuses on individual and household variables that affect use. In addition, our review includes past work exploring motives for water conservation.

6.1.1 Personal and Household Demographics

In the water research community, there is much interest in assessing the impact of various demographic variables on water usage. However, with a small number of exceptions (*e.g.,* Mayer *et al.*, 1999), researchers rarely have datasets that allow them to match household-level consumption data with rich demographic data about a home (*e.g.,* number of low flow-toilets, number of water using appliances/fixtures) and the people within it (Kenney *et al.*, 2008). In comparison, obtaining data on weather, price, and local legislation to compare with household usage is relatively straightforward. Taking into account the effect of demographic variables on usage is often challenging not just because of the difficulty in obtaining the data but also in isolating the effect of any particular variable. As Hamilton (1983) notes, many of the variables are correlated with one another (*e.g.,* personal income and house size) and have a complex network of interconnections.

Two of the most highly cited variables correlated with water consumption are household income and property type (*e.g.,* single-family home vs. apartment) (Jeffrey and Geary, 2006). Higher incomes allow for more discretionary use (*e.g.,* hot tubs, pools) and affluence is correlated with larger homes, which may have yards and gardens that require water to maintain. Stephenson (2003) presents a table of water usage according to standard of housing (p. 170), which shows that high quality housing areas used anywhere from 1.25x to 2.5x the amount of water compared to urban residential areas and low-cost housing. In addition, Russac *et al.* (1991) found that water demand was highest in homes vs. apartments/condominiums, which was attributed to low per capita outdoor watering in apartments and greater space for water consuming appliances in homes. Finally, Jeffrey and Geary (2006) cite a number of studies showing a positive correlation between water usage consumption amounts, property value and personal income.

Age and family type has also been correlated with consumption. In Russac *et al.* (1991), retired people in single-family homes consumed 52 gallons per day on average compared with 37 gallons per day by an adult living in a similar residence. The difference is likely because retired people are often in their homes for longer periods during the day (Memon and Butler, 2006). In addition, age-related diseases such as diabetes and prostate issues can increase the frequency of urination and therefore flushing (Green, 2003). Some of the highest indoor water usage comes from young families with a large number of children or from chronic medical conditions (according to Strang, 2004). Similarly, Mayer *et al.* (1999) also found that the presence of teenagers in a household tended to increase water usage.

It is not just the type of people living in a household that affects consumption but also the number living in the home. Although an increase in the number of occupants living in a home increases *total* water consumption, multiple studies have found that *per capita consumption* actually decreases (Butler, 1991; Edwards and Martin, 1995; Mayer, 1999)—see Figure 6.1. For example, in the REUWS study (Mayer *et al.*, 1999), a single person household used 1.5 times as much water on average than a two-person household and twice as much per capita than a four-person household (Figure 6.1a). This has implications for the prediction of future water demand, as much of the projected growth in the number of households over the coming decades in developed economies is expected to be from *single-person* households (Memon and Butler, 2006; Thames Water Utilities Limited, 2007). According to UK government projections, for example, the number of new homes is expected to increase by 3.3 million between 1996 and 2016 and the trend points towards smaller household sizes (EA, 2001; Figure 6.1b and c). Thus, water demands are expected to rise disproportionately higher than they would otherwise if just accounting for the total influx of population.

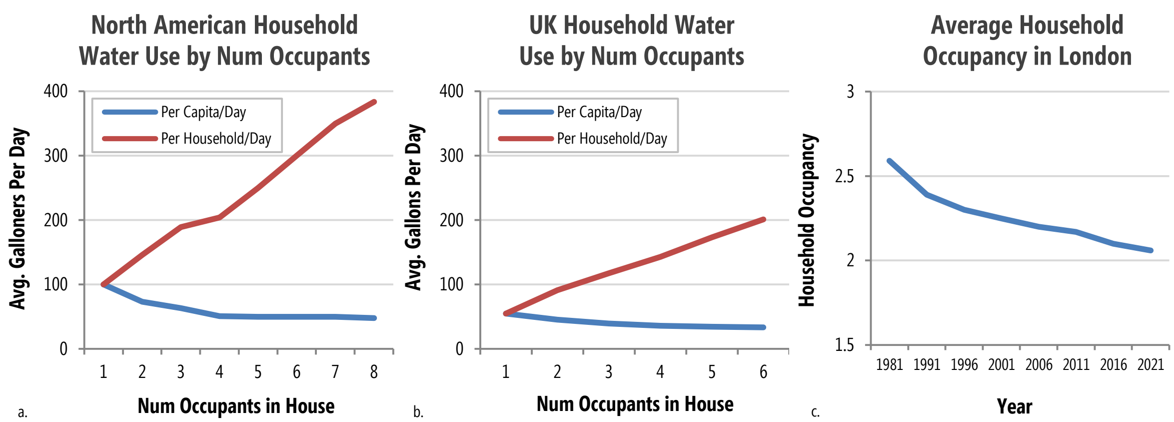


Figure 6.1: Although the overall amount of water used in a household goes up with increased levels of occupancy, the per-capita usage goes down. This pattern has been found in (a) North American homes and in (b) the UK. Some studies cite this trend along with observations that household occupancy levels are going down in some western cities such as London (c), which would lead to additional overall water use.

Finally, some past work has indicated that "behavioral knowledge" is an important predictor of water savings. That is, providing individuals with specific skills and knowledge about how to save water leads to a reduction in use (Corral-Verdugo, 2002 and Middlestadt *et al.*, 2001).

6.1.2 Time and Water Use

In this section, we move from discussing household and personal demographics to temporal effects. Depending on climate, seasonal variations affect water usage demand, a change that is generally linked to outdoor usage (Memon and Butler, 2006). For example, in the UK, garden watering took place every six days on average during the summer, using between 260-320 gallons per watering session (Herrington, 1996). In Seattle, water use can jump by 50% in the summer (Shridar, 1998). In the more arid Southwest, outdoor water demand can account for more than 90% of total use during the summer months (Gleick *et al.*, 2008).

At a more micro-level, different times of day correspond to higher and lower levels of water use. There are five distinct periods of water use: three peaks and two periods of lower flow. The sharpest peak is in the morning around 8AM followed by two smaller peaks corresponding to dinner time (around 7PM) and bedtime (11PM). The two lulls occur during the workday (10AM and 5:30PM) and while most people are sleeping (1AM and 6AM). As noted in Chapter 2, time-of-use pricing has been successfully employed to shift electricity usage peaks to periods during the day of lower demand, but no such strategy has been employed yet for water. Some governments, however, are investigating its potential (Turner *et al.*, 2010).

A few researchers have also explored temporal usage patterns of water at a disaggregated level (*e.g.,* Butler, 1993; Mayer *et al.*, 1999). When broken down by fixture category, showers tend to peak in the early morning with a mid-morning peak for washing machines. The other fixture categories (*e.g.,* faucets, dishwashers, toilets) have a two peak pattern with a spike in the morning and one in the evening. This overall domestic usage pattern is consistent in the UK (Butler, 1993) as well as North America (Mayer *et al.*, 1999). See Figure 6.2.

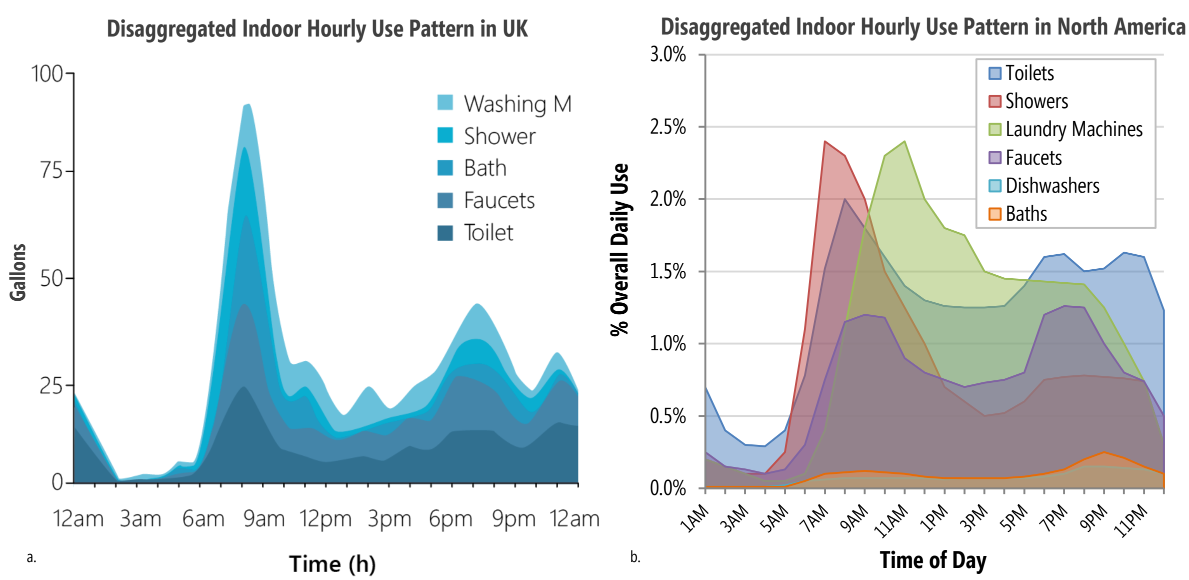


Figure 6.2: Indoor residential usage patterns in the (a) UK and (b) North America. Figure (a) is adapted from Butler (1993) while figure (b) is adapted from Mayer *et al.* (2009).

6.1.3 Gender, Culture and Religion

Although gender, ethnic background and religion have not received as much attention as the above factors (perhaps because their inclusion in research can be contentious and the variables themselves are difficult to obtain), there is evidence that these factors can also play a role in water usage. In Mexico, for example, Corral-Verdugo (2002) found that women consumed significantly more water than men. This was not a reflection of differences in how water was *perceived* by the two genders but rather that females had a higher level of involvement in chores that required water consumption (*e.g.,* washing dishes, watering plants, cleaning).

A set of studies by Smith and Ali (2006) looked at water usage behaviors based on ethnicity and religion. These studies are particularly good at illuminating the spiritual and ritual properties of water, an element that strongly differentiates water from other resources in the home. Smith and Ali logged (15-minute interval) water usage data along with census and interview data to explore water usage patterns in ethnically and religiously characterized London districts. They found pronounced temporal patterns particularly amongst the Muslim and Jewish communities. For example, in Jewish districts, there was a characteristic evening peak that varied throughout the year with the time of sunset (Figure 6.3a). The authors note that this peak is caused the Jewish 'Shabbat' (Saturday), which starts at sunset on Friday and no work may be done during this day. As might be expected, then, they also found that Saturday water use was much lower, on average, throughout the year compared with Friday or Sunday (Figure 6.3b).

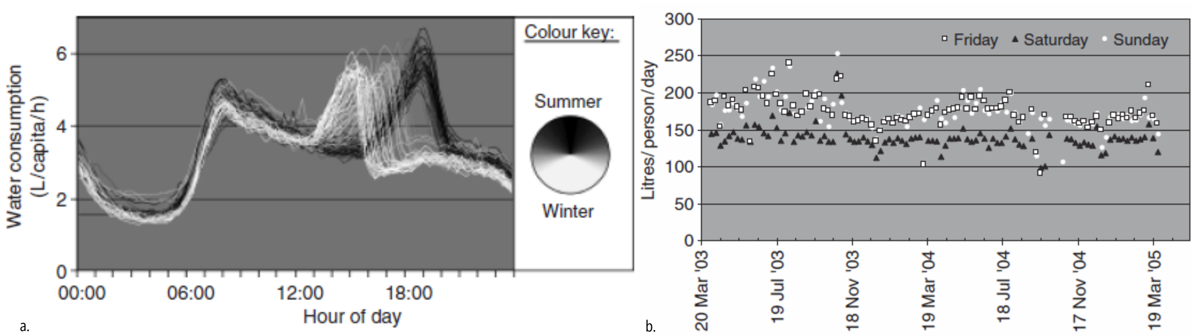


Figure 6.3: (a) In Jewish households, Smith *et al.* (2006) found a characteristic evening water usage peak that would shift with the time of sundown throughout the year as households prepared for the Sabbath ("Shabbat"), the day of rest. (b) Water use was much lower on Saturdays than on Fridays or Sundays. Both images from Smith and Ali (2006).

6.1.4 Water Use as a Routine and a Culturally Embedded Practice

Finally, water consumption has been examined from a sociological/anthropological perspective. Southerton *et al.* (2004) argue that most consumption in the home is *routine* and not subject to the forms of decision-making and reflection associated with the rational consumer (with aligns certain models of behavior described in Chapter 4). Medd and Shove (2005) highlight water consumption in particular (over other forms of home resource consumption) and contend that a "majority of domestic water use does not take place because of decisions made to consume water but rather as a consequence of the routines of everyday life."

For both Southerton *et al.* and Medd and Shove and many other sociologists, consumption practices in the home are not centered on the resources of electricity, water, or gas but rather the routine behaviors that draw from them. The resource itself is rarely the focus, only the enabler for behaviors. For water, these behaviors—washing up, taking a shower, doing the laundry—are often coordinated around other practices such as child-care, getting ready for work, and preparing meals (Medd and Shove, 2005). Thus, when thinking about informing water usage, one must consider not just water as a resource but also the larger set of interconnected activities and routines that are dependent on water in the home (indeed, connecting activities to consumption was a visualization technique we attempted in Chapter 9).

Larger social trends also influence household water consumption. In an essay on the rise of showering in the UK, Southerton *et al.* (2004) consider the complex infrastructural, technological, and social arrangements that have co-evolved to support cultural and social norms around cleanliness. Only recently in the UK has the daily shower begun to surpass the twice- or thrice-weekly bath. Indeed, Herrington (1996) observed that showering has risen steadily from 1976 through the 1990s. Southerton *et al.* (2004) cite key economic, technological, and infrastructural developments to support this practice. For example, it was not until the early 1930s that middle-class homes in the UK were equipped with hot and cold running water. These developments have also informed and shaped norms around washing and cleanliness. In the HCI community, Strengers (2008) recently addressed how smart metering systems may disrupt or otherwise impact comfort and cleanliness habits in the home.

6.1.5 Motives for Conserving Water

While the above subsections looked at factors influencing water usage in general, this subsection focuses specifically on the motives that people cite for *conserving* water. This has long been an interest of water utilities. In 1896, for example, the East London Company claimed “consumers took not the slightest interest in the … careful use of the water, and made no provision against drought, frost, or the breaking of the mains” (Trentmann and Taylor, 2005). Despite this interest, much of the research exploring motives for resource conservation has focused on recycling and electricity with much less attention paid towards household water consumption (Gregory and Leo, 2003; Corral-Verdugo *et al.*, 2003).

Most of the research exploring reasons for water conservation focus on economic or idealistic (*e.g.,* environmental) motives. Hamilton (1983) for example found that “the strongest single predictor of indoor behavioral conservation was idealistic motives; economic motives were relatively less important.” Hamilton explains that households with high income and citing predominantly economic motives for conservation were less likely to save water—except in those households of lower income. Others have found a similar emphasis on environmental motives. In a random phone-polling survey of 916 UK adults, 51% stated that environmental concerns were more important than personal financial concerns (Logica CMG, 2006).It is not always economic vs. idealistic motives, however. Corral-Verdugo *et al.* (2003) found that those with ecological water beliefs (*e.g.,* that water is a limited resource that needs to be conserved) used less water than those with utilitarian beliefs (*e.g.,* those who considered water an unlimited resource that could be used in an arbitrary way).

Finally, Kantola *et al.* (1983) note that motivating an individual to conserve water may not lead to reduced consumption if a number of criteria are not met including: if (1) the person does not possess the skills or knowledge to conserve water; (2) the household environment (*e.g.,* the influence of other household members) is not conducive to behavior change; or (3) conserving water is more difficult than the person envisaged. Thus, as we described in Chapter 4, a person's concern or positive attitude is an important correlate to engaging in proenvironmental behavior but is not necessarily enough to cause proenvironmental action.

6.1.6 Summary of Background Factors

Overall, this review shows that water consumption is influenced by a large variety of factors including affluence, culture, and temporal factors such as season or time-of-day. In particular, we differentiated water use from other types of home resources by offering that it more strongly notions of cleanliness, health and spirituality. We also presented factors, which influence conservation, such as financial vs. idealistic motives.

While our study below touches on some of these factors, the focus is to complement this body of work as well as the studies described in the *Water Management Programs and Strategies* in Chapter 2. In particular, we aim to explore specific areas that will help motivate and guide the design of water-based sensing and feedback systems. As such, we focus our attention on more directly examining specific knowledge gaps that exist around common water activities, looking at perceptions and practices around water bills, motivations that exist for limiting water usage and the type of feedback that people would like to see with regards to their water usage behaviors. All four areas have direct implications on future sensing and feedback systems for water.

6.2 STUDY METHOD AND PARTICIPANT DEMOGRAPHICS

To better understand water usage attitudes, knowledge, and practices in the home, we conducted a formative study consisting of an online survey of 656 North American respondents. The specific aims of this *Formative Water Survey* were to uncover conceptions and misconceptions of water usage in the home, to determine the ways in which people think about and respond to various forms of water conservation, and to explore opportunities for using HCI/Ubicomp to improve household awareness around excess or profligate use (*i.e.,* implications for the design of water-based eco-feedback technology).

6.2.1 Study Method

We recruited respondents via email lists, word-of-mouth, and online postings to Craigslist, Twitter, and Facebook. At the end of the survey, respondents could choose to leave their email address to be entered into a drawing for a single $50 Amazon gift certificate. There was also an optional checkbox that asked if this email address could be used to email the respondent once and only once for a follow-up survey (the *Display Evaluation Survey*, see Chapter 9). The survey was created and hosted using the online survey platform SurveyGizmo[29], which allowed us to use branch logic and our own custom HTML in the survey. Depending on branching, the survey asked between 38-45 questions. When possible, question order and answer order were randomized.

To thwart misuse, only one survey completion was allowed per computer. This was controlled via SurveyGizmo using cookies. Although abuse is a concern for any online survey, our analysis detected no overt forms of misuse or abuse. Given the number of open-ended qualitative questions in the survey, branching logic within the survey itself, the need to supply a unique email address to be entered into the drawing and the fact that an additional completion of the survey only earned the respondent one additional chance at the gift certificate drawing, we were unsurprised that abuse was not a problem.

Before launch, we pilot tested five iterations of the survey with seventeen participants. A majority of these pilot tests involved a research assistant sitting beside or behind the participant while they filled out the survey. The research assistant took notes on survey timing and comprehension but only engaged with the participant if s/he was struggling or had a clarifying question. From these pilot tests, we shortened the survey by approximately 15%, enabled branches such that question

[29] http://www.surveygizmo.com

wording and answer blanks were in the respondent's metric of choice (gallons or liters), and changed unclear wording.

At a high level, the survey was divided into four parts: the first part gathered information on personal and household demographics such as gender, income level, education, and information on house type (apartment/condo vs. house), number of bathrooms, number of residents, etc. The second part asked questions about the respondent's water supplier, their water bills, and their payment practices. The third part explored water usage attitudes, perceptions and behaviors including questions about *who* they perceive to use the most water in their home and why and questions about water usage amounts for everyday water use behaviors. The fourth and final part of the survey investigated the respondent's conservation and environmental outlook including questions on global climate change, the perceived eco-friendliness of the respondent's social groups, and their concern about water and why. Appendix B contains the full set of survey questions.

6.2.1.1 Data Analysis

Before analysis began, the survey data was processed to convert all volumetric responses to gallons (the survey allowed for either liters or gallons) and to convert monetary units to US dollars. Throughout the presentation of our results, we simplify five-point Likert-scale responses to three-point to make our figures more legible. Thus, a "Strongly Disagree," "Disagree," "Neutral," "Agree," and "Strongly Agree" scale was reduced to "Disagree," "Neutral," and "Agree." Our analysis was conducted on both the five-point scales and the three-point scales and our textual discussion includes both.

The four open-ended survey questions were coded based on the iterative coding method prescribed by Hruschka *et al.* (2004). Three researchers independently created initial sets of codebooks (one codebook per researcher per question) based on answers from a random sub-sample of 50 of the 656 respondents. The codebooks were then combined for each question and given to two new coders, who independently coded the same 50 respondents' answers. A Cohen Kappa's inter-rater reliability score was calculated on this data and the two coders met to discuss and modify problematic codes in the codebooks. The two coders then coded the entire set of open-ended responses using the updated codebooks. The Cohen Kappa's inter-rater reliability scores for these questions are Table 6.1. Finally, the coders met again to discuss discrepancies and make corresponding modifications to create a final dataset.

Question	Num Respondents	Num Codes	Cohen's Kappa Score	Lowest 3 Cohen's Kappa Scores (Ascending)	Highest 3 Cohen's Kappa Scores (Descending)
Why do you think this person uses the most water in your home?	545	16	0.77	"junk" (0.23), "environmental reason" (0.40), "other reason" (0.55)	"only one living there" (0.95), "long showers" (0.93), "takes baths" (0.90)
Why are you concerned about the water supply in your area?	198 (only asked if respondents previously indicated that they were concerned with the water supply in their area)	12	0.73	"junk" (0), "other" (0.57), "wasteful use" (0.71)	"growing population"(0.97), "drought" (0.96), "quality of water" (0.90)
Other measures taken to conserve water in the home not listed above.	262 (previous question listed strategies to conserve water, respondents could write-in a response if they utilized additional strategies not listed)	16	0.73	"junk" (0.24), "other installation" (0.30), "other" (0.44)	"take showers instead of baths" (1), "install more efficient fixtures" (0.96), "turn off water while doing activity" (0.95)
Other reasons for saving water.	88 (previous question listed reasons for saving water, respondents could write-in a response if one of their reasons was not listed)	16	0.62	"junk" (0), "cost" (0.38), "energy" (0.39)	"cost (sewage)" (1), "environmental responsibility" (0.88), "upbringing" (0.85)

Table 6.1: Cohen Kappa's inter-rater reliability scores for the four subjective questions coded in the Formative Water Survey. We followed the iterative coding process as prescribed by Hruschka *et al.* (2004). The scores presented here are from just after our two coders coded the entire set of open-ended responses. Once these statistics were computed, our coders met a final time to eliminate any discrepancies and provide a final coded dataset with 100% agreement.

6.2.2 Participant Demographics

We limited the survey to North American respondents because of regional differences in water availability, infrastructure and cultural norms and practices. Of the 711 total survey completions, 55 of these were from outside North America and thus were not analyzed for this dissertation. Of the remaining 656 respondents, 72 were Canadian (11%) and the rest were American (N=584). The average age of our survey respondents was 36.7 (SD=13.6; Min=18; Max=81) and 62% were female (N=407).

Given our recruitment method, we do not have a random sample of the North American population. The reliance on word-of-mouth and social networking sites led to a skewed demographic that was, in part, reflective of the research team's own composition (highly educated and in a technical profession). In addition, there is a self-selection bias in our sample in that these are people who saw the survey link and chose to click on it. The SurveyGizmo survey engine records HTTP referrer information. From this, we can surmise that 36.1% of respondents came from Craigslist and 13.9%

from Facebook or Twitter; the remaining 50% had no referrer information recorded. Although we received 711 survey completions, an additional 156 people started the survey but did not finish. This resulted in a drop-out rate of approximately 18%, which was lower than expected given the ease with which a person online can simply close the browser window to stop taking a survey.

Of the 656 completed surveys from North American respondents, the top five reported professions were: student (21%), education (11%), science/technology (10%), retired/homemaker (9%) and research (8%). The education levels were similarly skewed towards an educated population: 37% reported bachelor's degrees and 36% reported graduate degrees. In contrast, household income was relatively evenly spread across different income categories, though again this is not reflective of the general Canadian or US populations (DeNavas-Walt *et al.*, 2010). See Figure 6.4. We note this bias in our analysis and discuss this further in the Findings section as well as the Discussion section of this chapter.

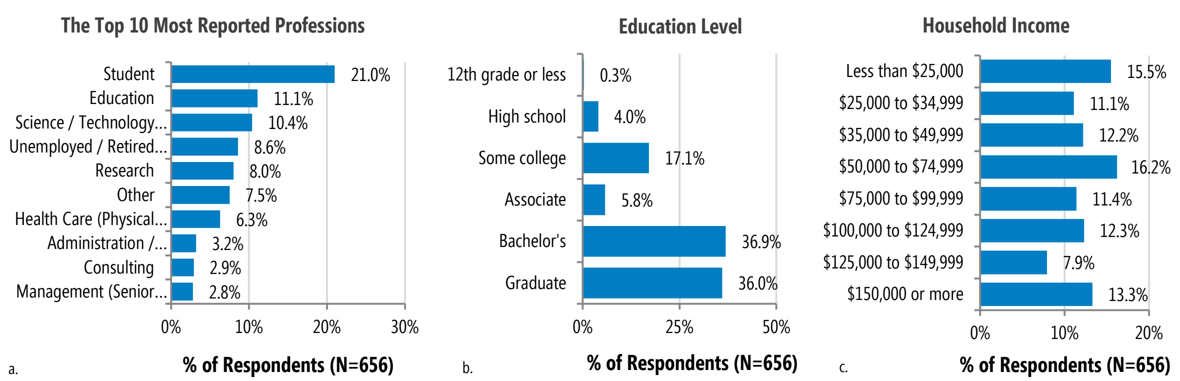


Figure 6.4: The demographic makeup of our survey respondents.

As noted in Section 6.1, household demographics such as household income, number of children in the household, housing type (*e.g.,* house vs. multi-family dwelling), and number of bathrooms are all factors that influence per capita consumption and are important to consider when examining perceptions and practices around water use. The average household size among our respondents was 2.8 (SD=1.5); 17.2% of respondents reported that they live alone. Of those respondents that reported having children in their household (31.8%), the average number of children was 1.7 (a child in this case was defined as anyone living in the home under 18 years old). The average number of bedrooms and bathrooms: was 2.9 and 2.0 respectively. In terms of housing type, 64.2% of our respondents reported living in a house while 35.8% reported living in a multi-family dwelling (*e.g.,* apartment or condominium). Overall, 46.3% of respondents reported renting their property—the rest own.

6.3 FINDINGS

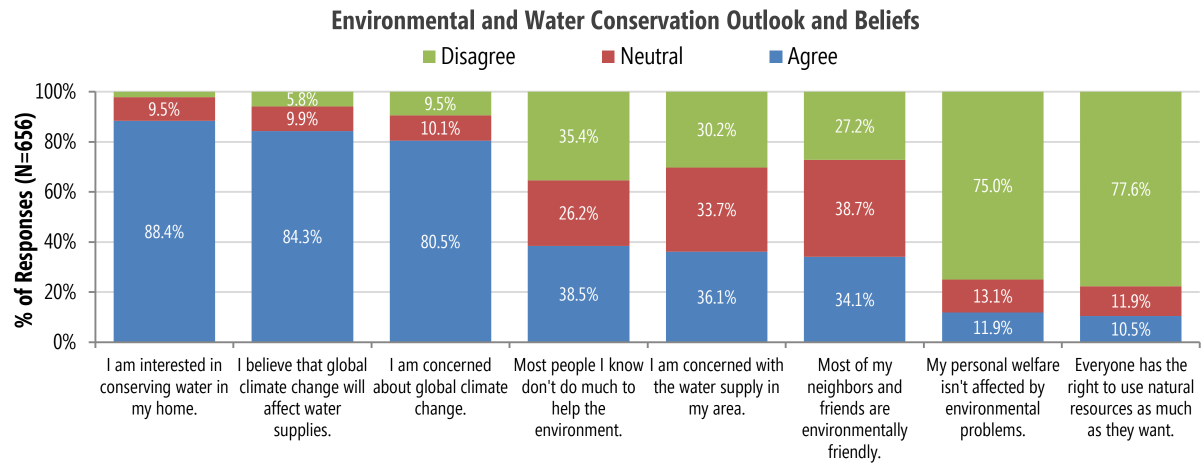
The primary focus of the survey was to investigate water usage awareness and knowledge, water conservation practices and motivations, and attitudes towards water and the environment. We present the results here with an eye towards implications for design of eco-feedback interfaces. These implications are relevant not just to ambient eco-feedback displays but also to utility websites and bills.

6.3.1.1 Environmental and Water Conservation Attitudes and Beliefs

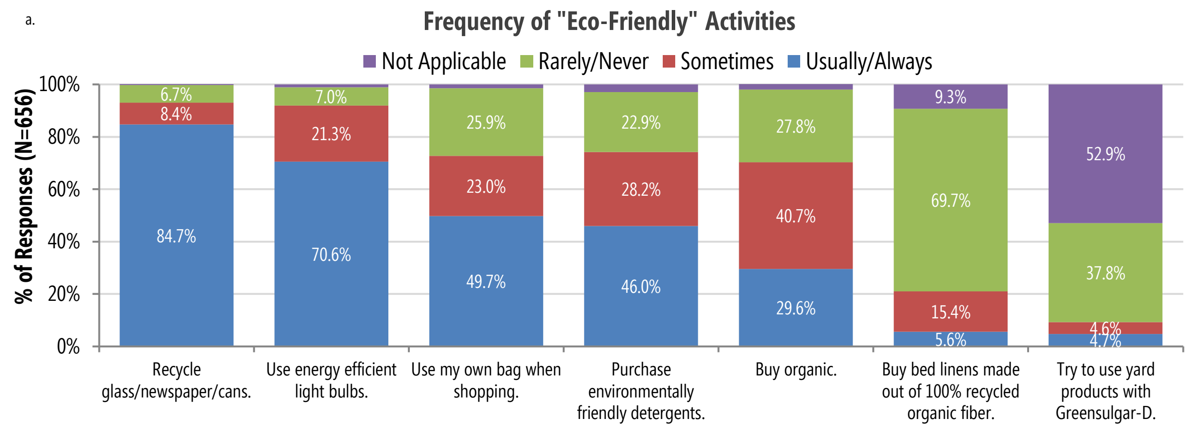
Given that our respondents were a self-selected population who voluntarily opted into taking a survey about water, it is not surprising that a large majority (88.4%) reported interest in conserving water in their home (Figure 6.5a). This self-interest in water conservation is an important factor to consider when reading our analyses and we discuss its implications on our findings. Respondents also had a general interest in the environment and engaged in various “eco-friendly” activities. For example, 80.5% reported concern about climate change and a large majority reported that they actively recycle and use energy efficient light bulbs in their home (84.7% and 70.6% respectively, see Figure 6.5b). Although most are concerned about the environment and believe that climate change will affect water supplies (84.3%), fewer are actually concerned with the impact of these issues on their own lives. A minority (36.1%) voiced concern with the water supply in their local area. For those that were concerned with their local water supply, the top three reasons included a general water shortage concern (34%), weather such as drought (24.2%), and the quality of their drinking water (16%).

We also examined perceptions of “greenness” amongst respondents’ *social groups* with the idea that this may further reflect on respondents’ proenvironmental tendencies. Given the general level of environmental interest among respondents, we were surprised that only 34.1% thought their friends and neighbors were “environmentally friendly” and 38.5% believed that most people they know “*don’t* do much to help the environment”. This has interesting implications for data sharing and social-comparisons in water usage feedback displays.

Finally, because our survey asked questions about behaviors and beliefs that had socially desirable responses, we included two questions to help evaluate social desirability bias. Social desirability “refers to a need for social approval and acceptance and the belief that this can be attained by means of culturally acceptable and appropriate behaviors” (Marlowe and Crowne, 1961). Past research studying proenvironmental behavior has found a social bias towards inflating one’s



a.



b.

Figure 6.5: (a) Likert scale responses to various statements about the environment and water. (b) Likert scale responses to statements regarding the the frequency of performing various "eco-friendly" activities. To simplify the visualization of these responses, the 5-point Likert scales were condensed to 3-point scales.

knowledge of environmental issues and engagement in various eco-friendly activities (*e.g.,* Hamilton, 1985). Finding and mitigating desirability bias is challenging when no external means of validation are available, such as in an online survey. Thus, we adopted a strategy employed by Berk *et al.*, (1993)[30] to include fictitious conservation activities and issues in one question of our survey. Responses to these fictitious items provide insight into the general bias within the respondent pool as well as to identify *individual* respondents particularly prone to bias. However, this approach is not without limitation—the key one being that the fictitious item or items may not be properly understood, prompting an incorrect response.

In our case, we included two fictitious items of our own creation on the frequency of "eco-friendly" activities question: "Buy bed linens made out of 100% recycled organic fiber" and "Try to use yard

[30] Berk *et al.* included seven fictitious items in their survey launched in 1991 in Southern California. Interestingly, two of their seven fictitious items could no longer be considered fictitious: recycling light bulbs and owning an energy saving television set.

products with Greensulgar-D[31].” Only 1.8% of respondents stated that they *always* buy the recycled bed linens and 1.5% *always* use Greensulgar-D (though 21% reported buying recycled bed linens some of the time and 9.3% reported using Greensulgar-D some of the time). These percentages indicate that there will be some inflation of positive responses due to social desirability bias. Though we did not conduct this analysis below, future work could use these fictitious responses as covariates to adjust downward the self-report data for questions with some social desirability.

Summary of Environmental and Water Conservation Attitudes and Beliefs

In summary, our respondents could largely be described as “green”—most had an interest in conserving water in their homes and many engaged in eco-friendly activities. In addition, we found a slight positive bias in questions that asked about socially desirable beliefs and behaviors. Both points should be considered when interpreting our results. In terms of implications for water eco-feedback systems, our respondents are a particularly motivated subset of the general population that would likely comprise the early-adopters of such systems.

6.3.1.2 Water Literacy/Knowledge

Past studies of electricity usage found that few people understand the units used to measure electricity consumption, namely watts and kilowatts and even fewer understand watt-hours or kilowatt-hours (Anderson & White, 2009; Kempton and Montgomery, 1982)[32]; however, no studies that we are aware of have previously explored similar comprehensions of water-related units. This has obvious implications for the ways in which consumption information is presented in eco-feedback systems. In our survey, we asked respondents to self-rank their own confidence in understanding various measurements of water including *volume measures*: gallons, liters and CCF (100 cubic feet, a standard measurement of water and natural gas among American utilities) and *flow-rate measures*: gallons per minute (gpm) and liters per minute (lpm). We also asked about two electricity related measures, watts and kilowatt-hours, to contextualize our water-related results.

The question was phrased as: “I feel confident that I understand each of the following measurements and could explain their quantity/definition to a friend.” As pointed out earlier, one of

[31] Whereas the first fictitious item was completely fabricated, the second fictitious item was based on Berk *et al.*, (1993): “use of yard products with Selgar-D.”

[32] Watts are a unit of power while watt-hours are a unit of energy. A watt measures how many joules of work can be done in one second while a watt-hour is the amount of energy that can be done with a one watt source of power for one hour. For example, a 100 watt light bulb burning for one hour consumes 100 watt-hours of energy. To make this more clear, one can draw an analogy between water and energy measurement units. The flow rate of water (*e.g.*, gallons per minute) is equivalent to watts and volume consumed (*e.g.*, gallons) is equivalent to watt-hours. A one gpm fixture filling up a large bucket for one hour will fill the bucket with 60 gallons of water.

the first questions in the survey asked respondents to select between either "gallons" or "liters" as their most comfortable water measurement unit. To make the presentation of our results more clear, we will break the responses down into two groups based on whether the respondent had previously selected "gallons" (N=542, 82.6%) or "liters" (N=111, 17%)—we refer to these as *native* units. The results are presented in Figure 6.6.

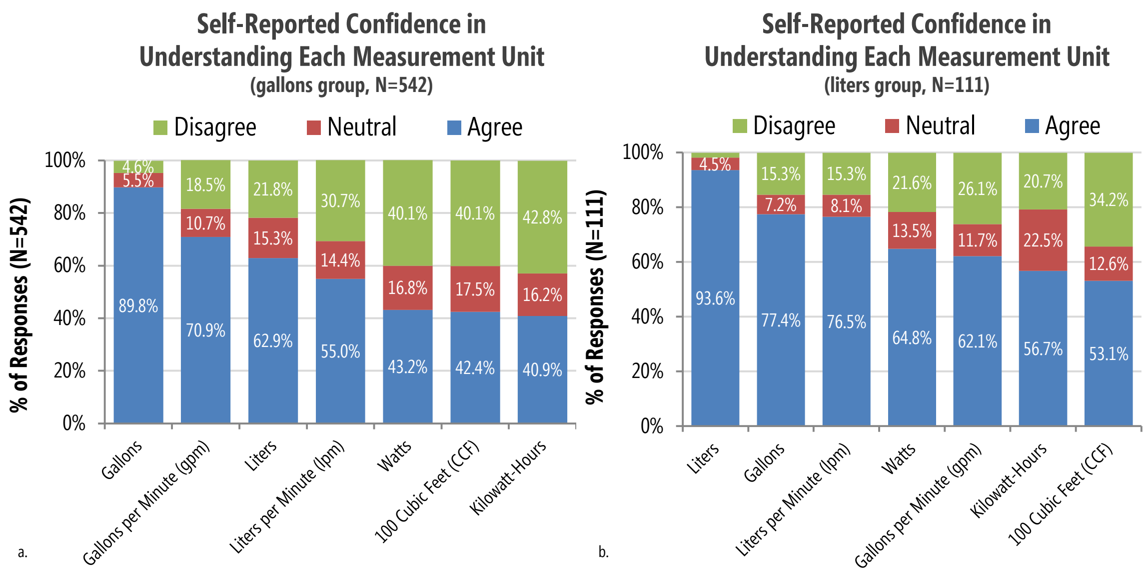


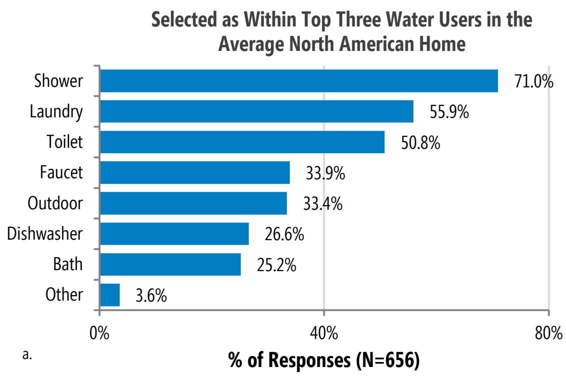
Figure 6.6: Self-reported confidence in understanding various measurements common to home resource consumption. The two graphs (a) and (b) present the same information but broken down by two groups: a "gallons group" (N=542) that previously indicated that they were more comfortable with gallons than liters and a "liters group" (N=111) that previously indicated more comfort with liters than gallons.

We expected that gallons and liters would be more comprehensible than other units (*e.g.,* gpm or watts) because of their physical embodiments in the everyday experience (*e.g.,* buying a one gallon jug of milk at the store). In contrast, energy related metrics have no such easily identifiable tangible manifestations and therefore remain abstract. As expected, we found that for both groups, the native volume measurement units were most understandable: 90% of respondents in the "gallons" group stated that they understood gallons and 94% in the "liters" group stated that they understood liters. However, when shifting from volume measures to flow-rate measures, there was approximately a 20% drop off in self-perceived understanding. Although gallons-per-minute and liters-per-minute are labels used on fixtures and appliances, they are not as well understood as their volume counterparts—perhaps because they are less tangible (*e.g.,* a bucket or gallon jug does not represent flow-rate well; the rate with which those containers fill does however). Finally, neither group understood CCFs despite it being one of the standard units of measurement for billing among utility companies (many water meters are also in CCFs). For comparison, CCFs were understood about as well as watts and kilo-watt hours. See Figure 6.6 for details.

We shift now from assessing respondents' understandings of measurement units to more holistic understandings of *what* contributes to water consumption in the home. Again, this inquiry has direct implications for the design of eco-feedback systems as it can help reveal areas that suffer from the largest knowledge gaps that eco-feedback may want to target. Past studies of residential end uses of water have found that outdoor usage comprises nearly a third of a household's total water usage (31.4%) (Mayer *et al.*, 1999; Vickers, 2001). For indoor use, the most water consuming fixtures/appliances are toilets, laundry machines, and showers accounting for 18.3%, 14.9%, and 11.5% respectively of a home's *total* usage (including indoor and outdoor, see Vickers, 2001). We asked respondents to rank what they believed to be the top three most water consuming fixtures/appliances in the *average North American home* (including outdoor water usage). We provided a list of twelve items to choose from. The results compared with the actual water use estimate in the average North American home are shown in Figure 6.7.

The most frequently selected item, shower, was ranked within the top three 71% of the time (it is 4th in Vickers' list). However, only half of respondents selected laundry machines and toilets as heavy water users (55.9% and 50.8% respectively). Outdoor water usage, which should have been ranked number one, was only within the top three 33.4% of the time though it was correctly selected as the number one water user by 120 respondents (18.6%). Dishwashers, which are the least water consuming fixture/appliance in the average North American home, were incorrectly ranked within the top three more than a quarter of the time (26.6%).

These results suggest that most of our respondents had an inaccurate conception of what fixtures and appliances accounted for most of the water use in a typical North American home. A potential limitation of this question, however, is that respondents may have answered based on their personal experiences with water usage *in their own home*. For example, those who rent or live in a multi-family dwelling may not perform any outdoor water usage activities, making that response an unlikely choice. Despite this limitation, the results, at the very least, indicate that respondents had difficulty thinking about general residential water usage patterns.



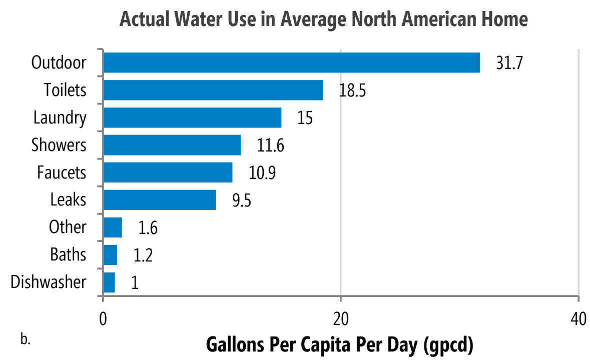


Figure 6.7: (a) The results from the question asking our respondents to rank the top three highest water users in the average North American home. (b) Actual water usage breakdown in the average North American home according to Vickers (2001).

To dive deeper into the water knowledge of our respondents and to bypass the need to ask about the abstract concept of "average North American homes", we created a set of questions about water knowledge that could be objectively evaluated. In particular, we asked respondents to estimate the water usage amounts of nine common water activities in the home. For each activity, an open-ended answer blank was supplied for the usage amount estimate along with a three-point Likert scale, asking for a confidence measure in the estimate ("Not at all confident," "Somewhat confident," and "Confident"). The answers here could be objectively quantified for accuracy. The results are presented in Table 6.2, Table 6.3, and Figure 6.8. Given the wide variation in responses, we found the median to be a better indicator of general estimate trends than the mean (see Table 6.2).

In general, respondents tended to *underestimate* water usage activities. For example, the average American bathtub holds 45 gallons of water filled to the overflow valve (WECalc, 2001). Our respondents estimated that the median bath used less than half of this—20 gallons of water. Similarly a 10-minute shower with a standard 3 gpm showerhead uses approximately 30 gallons of water (10 x 3 gpm = 30). The median response in our survey was 20 gallons, which is an underestimate of 33%. A low-flow showerhead reduces this 30 gallon shower down to 25. However, here, perhaps influenced by the word "low-flow," our respondents provided an even lower estimate: a median response of 10 gallons (an underestimate of 60%). The most glaring underestimate, however, was with regards to outdoor lawn watering. The question asked for respondents to estimate the amount of water used by a standard oscillating yard sprinkler for 1-hour. The median response was 20 gallons; however, the actual usage is *6 to 24 times as much*—between 120 gallons for a 2 gpm low-flow sprinkler to 480 gallons for a high flow version (8 gpm).

	Minimal Outliers Removed				3xInterquartile Range Outliers Removed			
	Mean	Median	SD	% Remvd	Mean	Median	SD	% Remvd
Bath	29.3	20.0	37.1	0.5%	23.2	20.0	16.9	5.1%
10-Min Standard Shower	28.2	20.0	39.2	0.2%	21.2	16.5	16.8	5.7%
10-Min Low-Flow Shower	18.1	10.0	29.9	0.8%	13.7	10.0	11.7	4.3%
Dishwasher	16.1	8.0	38.5	2.2%	10.1	8.0	8.1	7.8%
Hand Washing Dishes	9.0	5.0	13.4	0.5%	7.0	5.0	6.3	4.0%
1-Min Bathroom Tap On	3.2	2.0	6.8	0.6%	1.9	1.3	1.5	7.1%
Standard Toilet Flush	5.5	3.0	22.5	0.2%	3.7	3.0	2.5	3.4%
Low-Flow Toilet Flush	2.7	1.5	7.3	1.1%	1.8	1.5	1.3	5.9%
1-Hr Stand. Yard Sprinkler	42.3	20.0	79.2	1.7%	29.8	15.9	33.1	5.6%

Table 6.2: The water usage estimates of nine common water usage activities. The left half of the table has a minimum number of outliers removed: all zero responses and two grossly inaccurate estimates: a 1,000 gallon estimate from hand washing dishes and a 222,222 gallons estimate from yard sprinkler. The right part of the table removed data points outside of the "lower" and "upper outer fence" ($Quartile_{25\%}$ - 3 x Interquartile Range and $Quartile_{75\%}$ + 3 x Interquartile Range) according to the *NIST e-Handbook of Statistical Methods (NIST, 2010)*. Note that this drops the mean and standard deviations due to a few dramatic overestimates in the original dataset. The medians, however, are not substantially affected.

	Median Estimate	Accurate Low Estimate	Accurate High Estimate
Bath	20	34 gal (45 gal tub filled 75%)	45 gal (45 gal tub filled to overflow valve)
10-Min Standard Shower	20	30 gal (3 gpm showerhead)	50 gal (5 gpm showerhead)
10-Min Low-Flow Shower	10	20 gal (2 gpm ultra-low-flow showerhead)	25 gal (2.5 gpm low-flow showerhead)
Dishwasher	8	7 gal (1995-present)	12-14 gal (1980-1995)
Hand Washing Dishes	5	Answer greatly dependent on kitchen faucet flow rate and user behavior (*e.g.,* whether a wash bin is used or faucet is on entire time dishes are washed as well as the number of dishes). With a low-flow faucet (2.5 gpm), a reasonable low estimate might be 5-7 gals and high estimate 15 gals.	
1-Min Bathroom Tap On	2	1.5-2.5 gal (2.5 gpm max allowed after 1994)	2.75-3 gal (2.75-3 gpm from 1980-1994)
Standard Toilet Flush	3.0	3.5 gpf (toilets from 1980-1994)	5.0 gpf (toilets from 1950s-1980)
Low-Flow Toilet Flush	1.5	1.0 gpf (ultra-low-flow toilets, not common)	1.6 gpf (1.6 gpf max allowed after 1994)
1-Hr StandYard Sprinkler	20	A single rotating lawn sprinkler, on the low end, might use 2-4gpm resulting in 120 to 240 gals of water used.	A single rotating lawn sprinkler, on the high end, might use 5-8 gpm resulting in 300 to 480 gals of water used.

Table 6.3: Comparing median water usage estimates provided by respondents to actual usage estimates. Sources: Mayer *et al.*, 1999, Vickers *et al.*, 2001 and WECalc, 2011. A US federal requirement for residential fixture flow rates was instituted in Jan 1st, 1994 allowing a maximum of 2.5 gpm for faucets and showerheads and 1.6 gpf for toilets installed after that date.

The most accurate responses were for estimating toilet flushes (*e.g.,* median low-flow estimate: 1.5 gpf vs actual: 1.6gpf) and for estimating the amount of water used in 1-minute by a common bathroom faucet (median estimate was 2 gallons). Of course, these are *per-use estimates* and do not account for how frequently each use occurs. As we saw from Figure 6.7, only 50% of respondents selected toilets as heavy water users despite them being the number one indoor water consumer in the average home. So, although respondents were fairly accurate in assessing the amount of water used per flush, this knowledge did not necessarily translate into understanding general usage patterns in the home. Interestingly, although dishwashers are often selected as heavy water users,

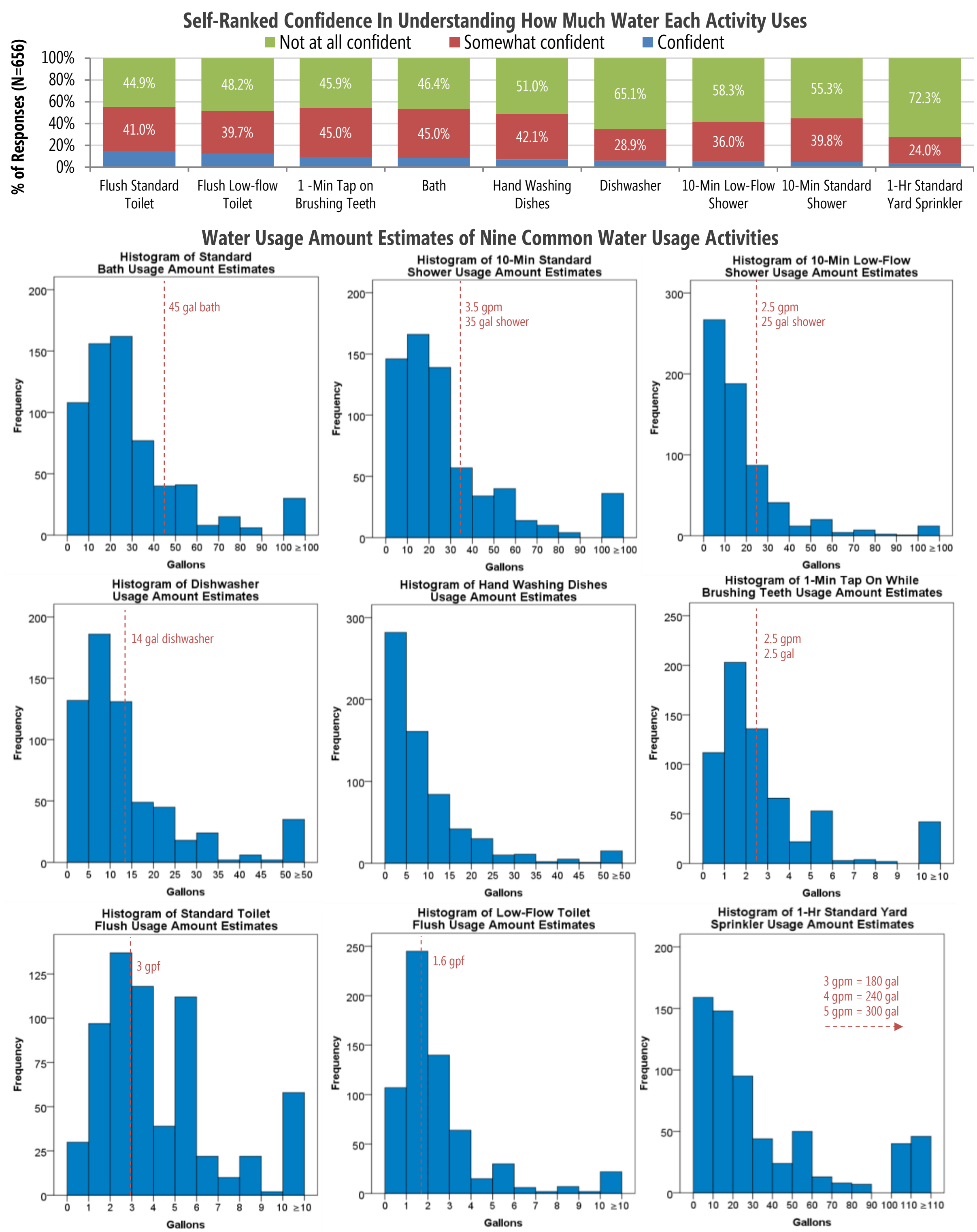


Figure 6.8: (top) The confidence ranking supplied for each water usage amount estimate. (bottom) The water usage estimates for nine different activities ranging from a flushing a low-flow toilet to using the dishwasher. The dotted red line indicates *an accurate response*. No such line is provided for "hand washing dishes" estimates because these could vary greatly depending on faucet type and whether water flowed continuously or was turned on and off. In general, respondents were not confident in their estimates and tended to *underestimate* amounts.

the actual water usage estimates for one load of dishes in the dishwasher were not far off. The median was 8 gallons per load while an accurate response would be between 7 to 14 gallons depending on the dishwasher model.

So, for the most part, respondents generally had a limited understanding of the amount of water common water usage activities consume, particularly for showering, bathing, and lawn watering. Examining the accompanying confidence ratings, we found that most respondents professed low confidence in their estimates, indicating they were aware their estimates may be inaccurate. Of the nine activities, only two received a "Confident" ranking more than 10% of the time: flushing a standard toilet (14.1%) and flushing a low-flow toilet (12.1%). The lowest ranking activity was lawn watering, which received a "Confident" ranking by 3.7% of the respondents.

Finally, we asked our respondents to compare their water usage with other households, 31% felt that they used less than average, 58% stated that they used average amounts, and only 11% thought that they used more than average. Although there is no way to evaluate the accuracy of these claims, eco-feedback could be used to more explicitly inform people about how much water they use compared to others (*e.g.,* a social normative comparison such as that offered by OPower: Laskey and Kavazovic, 2011).

Summary of Water Literacy/Knowledge

Even with a highly educated and self-interested population, our findings suggest that residential water usage knowledge is relatively low. Our results show not only that respondents had difficulty ranking the relative water usage amounts of common fixtures and appliances but also that they had limited knowledge of how much water common activities in the home use (*e.g.,* showering, lawn watering). This lack of knowledge would make it difficult for home occupants to understand and prioritize where they can conserve water in the home—indeed, it may lead to poorly invested effort. These results help motivate the need for better water feedback systems in the home—in particular, systems that are capable of providing information at the fixture or fixture category level and making recommendations about where to best save water.

6.3.1.3 Paying for Water

As noted in the introduction to this chapter, despite a recent prevalence of commercial off-the-shelf devices that provide real-time feedback on a home's electricity usage (*e.g.,* The Energy Detective), no such products exist for water. Thus, the water bill remains the primary—and most often only—

means of receiving feedback on water consumption. We were interested in exploring understandings of water cost, how water cost was perceived to influence consumption behaviors, and practices surrounding the reading and use of the water bill itself.

Of the 656 respondents, 439 reported that their household pays for water (67%). The primary reasons supplied for *not* paying for water were because the respondent lived in a multi-family dwelling that does not receive a water bill (24%) or because the respondent was on well water (3%). Thus, a rather large number of our respondents (33%) received no monitoring or feedback about their water consumption.

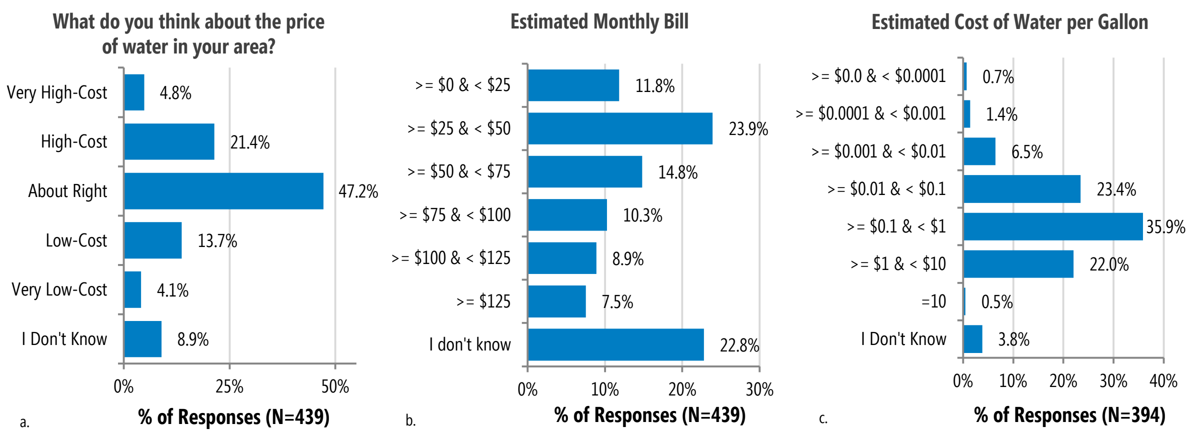


Figure 6.9: All three questions in the above figures were asked of respondents who previously indicated that their household pays for water. (a) Perceptions of the price of water in the respondents' local area. (b) The estimated monthly bill. (c) The estimated cost of water per gallon.

According to the US Environmental Protection Agency, the average US household spent $474 on their water bill in 2002 (Mehan, 2003 as cited in EPA, 2009), or about $40 per month. For comparison, the average US household spent $104.52 on their electricity bill in 2009—$87.65 when adjusted for inflation to 2002 levels (U.S. Energy Information Administration, 2011). Thus, electricity is over two times as expensive for most households compared with water—if the household even pays for water. For those 439 respondents that reported receiving a water bill, the average reported water bill was $68 per month (median=$50) or about $815 a year. Without knowing the actual bill amounts of our respondents, we cannot speculate about the accuracy of their estimates but the average and median seem reasonable given inflation and higher water costs since 2002 and the higher-than-average education and household income levels among our respondents compared to the general US population (the latter of which correlates with higher water use).

In addition to estimating monthly water costs, we also asked those respondents who previously reported receiving a water bill to estimate the price of water *per* gallon or liter in their home[33]. Although prices can vary depending on region, the average American pays $2.50 per 1,000 gallons or approximately $0.0025 per gallon—four gallons for a penny (Glennon, 2009). In our survey, we also asked that the respondent not consult a bill, an online website or other outside source for information because, we emphasized, we were interested in studying *their* perception of water cost. The question was open-ended so as not to bias the response but an “I Don’t Know” option was available for those who did not feel comfortable offering an estimate.

Figure 6.9c shows the responses. Note that the y-axis is plotted on a logarithmic scale because of the wide variation in estimates. After filtering the 24 outliers above $10 per gallon, the average price across the remaining responses was $0.79 per gallon (median=$0.20; min=$0.00001; max=$10). Both the average and the median *are off by a factor of 100* in comparison to the national average. Only 14% of the respondents’ estimates were 1 cent or less (the most accurate response). We also asked respondents to supply a confidence ranking for their estimate, either: “Not At All Confident,” “Somewhat Confident” or “Very Confident.” A large majority of respondents (71.3%) responded “Not At All Confident.” Interestingly, those that responded “Very Confident” (3.8%) offered similar estimates to the other two confidence groups. The cost estimates were also similar regardless of whether respondents were the primary bill payer or not (69% and 72% respectively).

There is obviously a substantial difference between the estimated cost of a gallon of water supplied by our respondents and the actual cost. There are likely multiple reasons for this difference. Compare water to gasoline for example: it would be highly surprising if estimates of gasoline cost per gallon were off by an order of 100. Unlike gasoline, however, water is relatively cheap—especially when considered in per-gallon units—which may not compel enough interest for a household to pay attention. In addition, the cost per gallon may not be listed directly on a water bill making the cost per gallon seem obscure. Finally, an accurate response to our question required that people think of cost in terms of a fraction of a cent, an uncommon conception of money.

Interestingly, however, there is some past precedence for our results, though not for studies of water. Becker *et al.* (1979) found similar results with the cost of electricity: in a study of 43 well-

[33] As noted previously, branch logic in SurveyGizmo was used to ask questions in the respondents’ unit of choice (*e.g.*, liters or gallons). Thus, questions were phrased according to gallons or liters and price amounts could be entered in the respondent’s currency of choice. All data was converted to gallons and $USD for our analysis.

educated households in Princeton, NJ, few households could accurately give the price of a kilowatt-hour of electricity. Answers ranged from \$0.03 to \$5.00, with a median of \$0.31 (the correct answer was \$0.05 but only 16% guessed \$0.10 or under).

Summary of Paying for Water

Unlike in the *Water Literacy/Knowledge* subsection where our respondents *underestimated* the amount of water used by common activities, here our respondents vastly *overestimated* the actual cost of water. This has implications for the way in which information about water consumption is presented. For example, if a resident is economically motivated to conserve, an eco-feedback system for water that draws attention to its cheap cost may actually provoke an increase in consumption. This is in contrast to common electricity displays, which often place cost as the primary focus (perhaps because electricity is more expensive than water).

6.3.1.4 Looking at the Water Bill for Feedback

Modern water bills provide more information than just the total due. In this section of the survey, our questions investigated what information the bill payer looked at on the bill as well as what other information they were aware of (Figure 6.10). This analysis focuses on the 256 respondents (40.4%) who reported that they were the *primary* water bill payer in the home. A large majority (90.6%) spend 5 minutes or less looking at the water bill—5.7% admitted to not even looking at it (*i.e.,* using auto-pay). When the bill *was* read, the most common information looked at was the total due (89.5%) followed by the overall water volume used during the pay period (62.3%). A minority of respondents looked at the overall cost of water used (39.3%), their sewer charge (31.9%) or the rate charge per unit of water (26.5%). This last result may partially account for why respondents were so inaccurate in estimating the per-gallon charge for water.

In addition, many bills provide information beyond cost to contextualize a household's water usage. For example, some bills include a bar graph that shows per-month water use over the past year to give occupants an idea of trends in their water usage (*e.g.,* whether they are using more or less than usual). Traditionally, the water industry has lagged behind the energy industry in implementing these sorts of advanced billing strategies, which can be used in demand side management programs

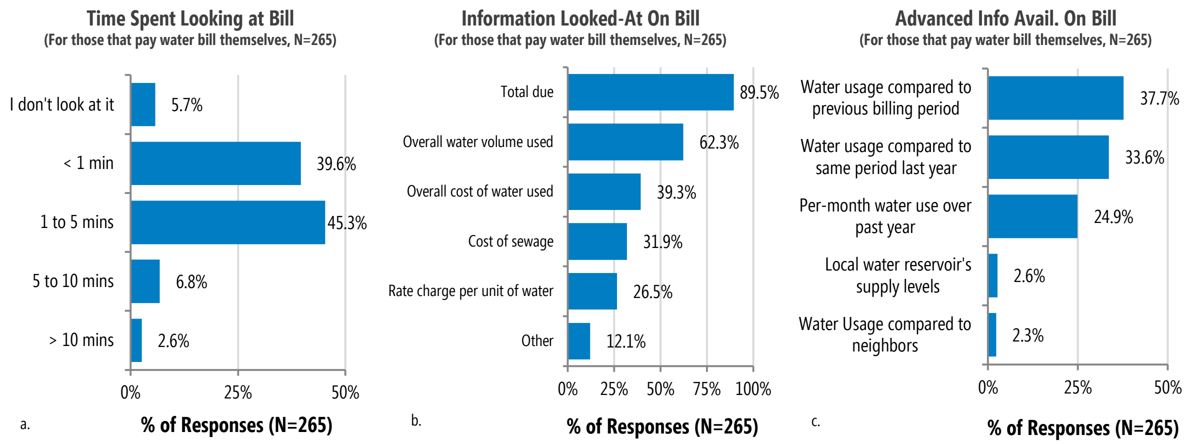


Figure 6.10: For those that indicated that they were the water bill payers in their household: (a) the time spent looking at the bill; (b) the information looked at on the bill; and the advanced information available on the bill.

to decrease per-capita consumption (*e.g.,* OPower's redesigned bill exists for energy but not water: Laskey and Kavazovic, 2011). Our results show that at least a third of bill payers received one or more types of advanced information on their water bills. The most commonly reported elements were "water usage compared to the previous billing period" (37.7%), "water usage compared to the same period last year" (33.6%) and "per-month water use over past year" (24.9%). Far less common, however, were indications of the "local water reservoir's supply levels" (2.6%) and graphs or data comparing water usage to neighbors (2.3%). So, the takeaway here is that people are generally not receiving much additional information on their water bills about their usage patterns. This is an opportunity for eco-feedback systems.

Finally, we also explored what information, if any, our respondents were interested in seeing about their water usage (Figure 6.11). Unlike the above questions in this subsection, we asked this question of all 656 respondents. There was a strong preference towards seeing self-comparison data and less interest in seeing social-comparison data. The most popular response was providing information on how water usage compared to the same period during the previous year (82.7%; 42.5% strongly agree) followed by water usage compared to the previous billing period (80.3%) and a graph of per month water use over past year (79.7%). Fewer respondents were interested in seeing their local water reservoir's supply levels (66%) or how their water usage compared to their neighbors (66%).

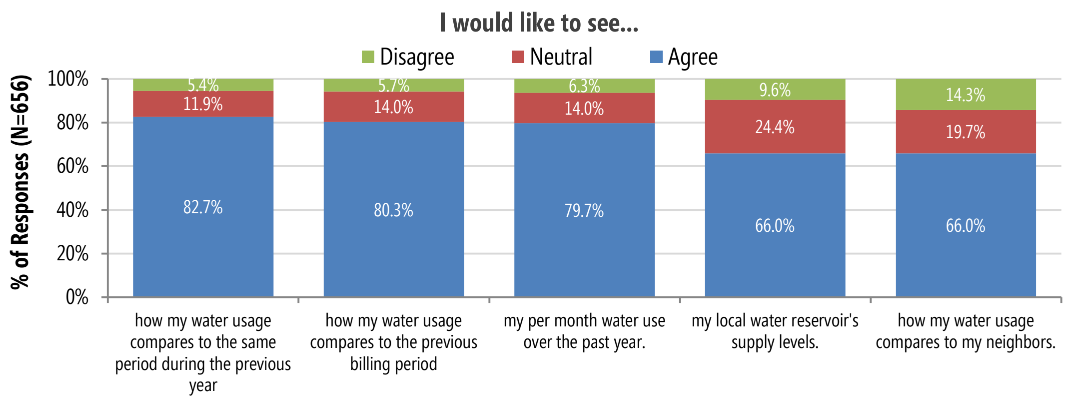


Figure 6.11: Interest in seeing various water usage feedback: self-comparison was generally preferred over social-comparison.

Summary of Water Bill Findings

In summary, we found that only 67% of our respondents reported that they receive any type of feedback on their water consumption. For those that do and consider themselves the primary bill payers, we found that most (90.6%) spend five minutes or less looking at their water bill and few actually receive advanced information on their water bill that would allow them to compare their usage to the past or others. This is in spite of our findings that a vast majority of our respondents are interested in seeing just this type of data.

6.3.1.5 Water Conservation Actions and Factors Influencing Consumption

As noted in the demographic section of this analysis, respondents were generally more proenvironmental than not and had an interest in water conservation. Given this interest, how often do people perceive themselves as trying to limit their water use? We found that 14.9% of respondents reported that they *always* try and limit their water usage and 84.4% do so at least half the time. Only 3.8% of respondents stated that they never try to limit their water usage (Figure 6.12b).

To gather data on what concrete steps people take to limit usage, we presented a list of approaches to limit water usage in the home and asked respondents to select the frequency with which they employ these approaches via a five-point Likert-response ranking from “Never” to “Always” with an additional “Not Applicable” response (Figure 6.12a). The most common response was waiting until there is a full load of dishes or clothes before starting the dishwasher or laundry machine (88.3%). The second and third most common techniques were turning the tap off while brushing teeth (77%), and turning the tap off when washing dishes (57.3%). Our respondents were much less likely to reduce the number of showers or baths that they take (28.1%).

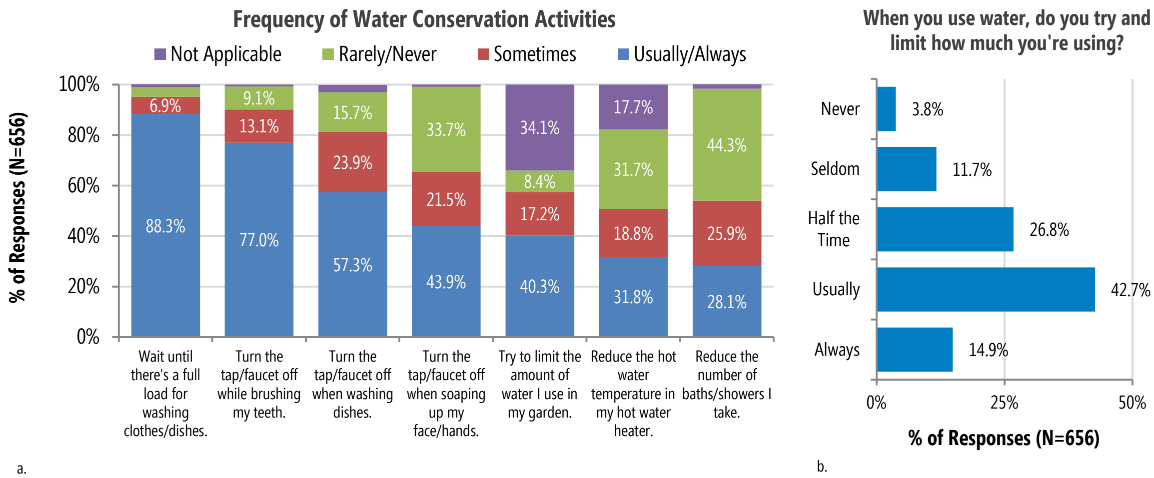


Figure 6.12: (a) The reported frequency of various water conservation activities. The question was closed-form with a five-point Likert-scale from "Rarely" to "Always," which was condensed to a three-point scale to make this graph more readable. (b) The reported frequency of trying to limit the amount of water use in the home.

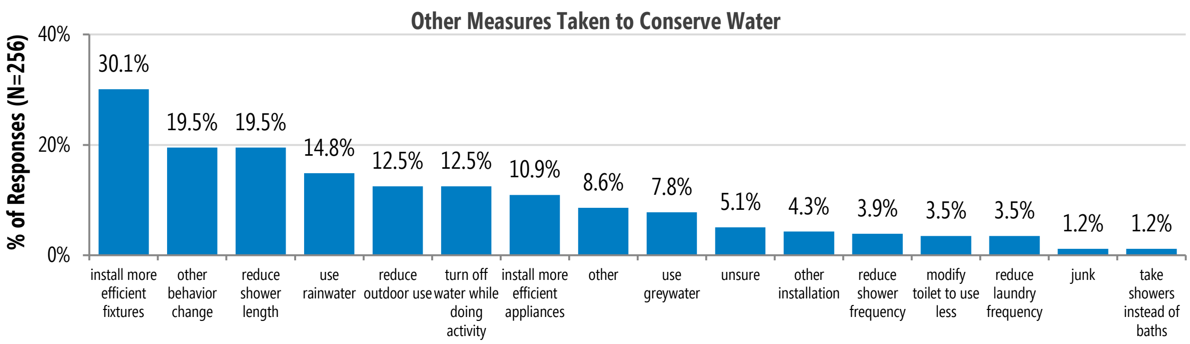


Figure 6.13: The coded responses to the question "Other reasons for saving water" that were not listed in the "Frequency of water conservation activities" question.

Nearly half of our respondents (47.7%) stated that there were other water conservation measures that they were aware of but that were not listed in the "frequency of various water conservation activities" question. A subset of these respondents (N=256) opted to write-in a response describing the measures that they take to conserve water, which were coded according to the method described in the Study Method section. The results are presented in Figure 6.13. The number one cited response was "installing more efficient fixtures" (30.1%) followed by "other behavior change" (19.5%) and "reduce shower length" (19.5%).

For those respondents who previously indicated that they try to limit their water use in some form (N=624), we asked about what reasons they considered when limiting their use (Figure 6.14a). The number one factor cited was environmental concerns (77.7%) followed by current weather conditions such as a drought (55.3%). A little less than half of respondents considered requests to conserve by their water supplier (48%) or laws or city mandates (41%). Far fewer thought about the cost of water (35.6%) or the cost of sewage (25.6%). For those respondents that reported being the primary water bill payer in their household (N=265), 46.8% stated that the amount they spend on their water bill influences their water usage behaviors (Figure 6.14b).

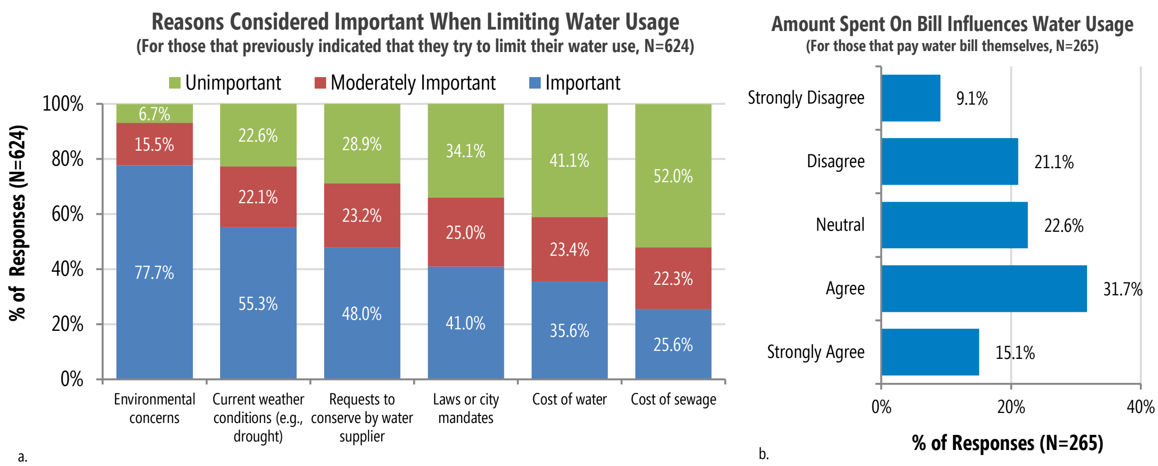


Figure 6.14: (a) Reasons considered important when limiting water usage, which was asked only if the respondent had previously stated that they try to limit their water usage at least some of the time (N=624). (b) Graph showing whether the amount of money spent on a water bill influences water usage behaviors. This question was asked only for those respondents who previously reported paying the water bill themselves (N=265).

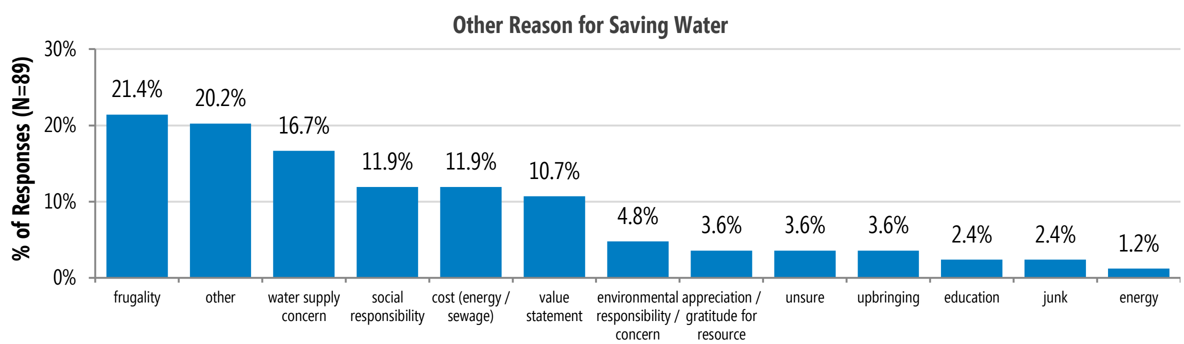


Figure 6.15: The coded responses to "What other reasons do you have for conserving water."

A subset of respondents (N=89) wrote-in an additional reason for limiting their water usage, which we coded using the method described in the Study Method section. The codes and their frequency are listed in Figure 6.15. A sense of frugality (*i.e.,* prudence in avoiding waste) was the number one reason for conserving water cited in 21.4% of the responses. For example, R229 mentioned "I generally don't like to waste things" and R571 "I have a general aversion to seeing anything being wasted." The third most cited reason was a concern about the water supply (*e.g.,* R256: "I live in a desert area").

Summary of Water Conservation and Factors Influencing Consumption

Although most of our respondents reported trying to limit their water usage, strategies to do so varied. Most commonly, our respondents focused on small, physical curtailment behaviors such as filling up the laundry machine or dishwasher before use or turning off the tap during an activity. Changing showering/bathing practices was much less common as was installing new, more efficient fixtures. In terms of motives for conserving water, a large majority of respondents cited environmental concerns—far more than those that cited cost. Although this may be a representation of the overall "greenness" of our respondent pool, past work found similar results (Hamilton, 1983; Logica CMG, 2006). Thus, a water-based eco-feedback system may want to emphasize weather, local watershed health, and reservoir levels over cost.

6.4 DISCUSSION

This chapter was concerned with investigating perspectives, understandings, and knowledge of water usage in the home. It was meant both as a formative study to influence the design of water feedback systems—for example, by gathering data on what sort of measurement units people are familiar with—as well as to uncover new opportunities and potential for water eco-feedback systems in general.

We found ample evidence to support the need for different sorts of water feedback than is currently available in most homes. A substantial portion of respondents (33%) received no monitoring or feedback about their consumption whatsoever, either because they live in a multi-family dwelling such as an apartment or condominium or because they are on well water. Interestingly, many multi-family dwellings do not have the metering technology to monitor each unit's consumption, likely because the cost of sub-metering hardware and installation is simply too high to justify its use. There is an opportunity here, then, for low-cost sensing technology that a motivated resident can install him/herself to receive water feedback. This system need not be controlled or monitored by the water supplier/utility but instead could be a private device that is solely owned and maintained by the homeowner (similar to The Energy Detective (TED) for electricity). We describe such a system in Chapters 7 and 8.

Our findings also suggest that most people have an inaccurate conception of what fixtures and appliances typically use the most water. For example, approximately a quarter of respondents ranked dishwasher and bath among the top three water consumers in the home, while these two sources typically account for only a very small portion of water use per capita in the United States

(Vickers, 2001). What's worse, respondents tended to *underestimate* the amount of water common activities consumed, particularly for showering, bathing, and lawn watering.This disconnect between knowledge and actual consumption points to the potential of eco-feedback displays to help educate, inform and potentially promote more efficient water use.

In terms of the ways in which this feedback should be presented, our findings suggest that volume measures such as gallons or liters (as preferred by the respondent) were better understood than flow rates (*e.g.,* gallons-per-minute). Interestingly, CCFs, which is the unit commonly used in meters and bills in the US was the least understood water-related unit. However, even though respondents tended to report high confidence of understanding in the volume measures, they had great difficulty applying this knowledge to water usage in the home. There is something much less tangible about water flowing down the drain than there is about water filling up a bucket—eco-feedback can play a role in crystallizing use and making it seem more concrete.

Comparison is a well-known and effective strategy in motiving behavior but seems underutilized in the water industry. In our study, we found that 27% of respondents had some sort of comparison on their water bills (*e.g.,* a per-month bar graph over past year, a comparison to last month, or a social-comparison to neighbors). We also found that, in general, respondents were more interested in self-comparisons than social-comparisons. For example, 83% of respondents expressed interest in seeing how their usage amounts compare to the same period during the previous year while only 66% were interested in seeing how their water usage compared to their neighbors.

Among other reasons, water is unique from natural gas and electricity because of its low cost. This distinction, more than any other, may lead to different emphases in water feedback displays in comparison to energy feedback displays. A vast majority of respondents overestimated the price of water—both the average and the median *are off by a factor of 100* in comparison the national average. Perhaps related, many more people cited environmental concerns as an important motivator for conserving water (78%) compared with those who cited cost (36%). Even though our respondent population was heavily biased towards positive attitudes and beliefs regarding the environment, this finding is consistent with past work (Hamilton, 1983; Logica CMG, 2006). Future work should explore how the differences in cost between water and electricity as well as the different perspectives of these resources (water often evokes more environmentally charged responses) should be leveraged in eco-feedback designs.

The greatest resource in a home is, perhaps, occupant attention. Most people lead extremely busy lives filled with professional and domestic responsibilities. Water is but a small part of this. In our survey, we found that a majority of primary bill payers (90.6%) spend five minutes or less looking at their water bills and almost half look at it for less than one minute or not at all. Thus, an eco-feedback system must be designed to be used and understood *at a glance*. For an ambient system that is highly visible in a home (*e.g.,* in the kitchen), one could probably expect a few glances a day at the most (30-60 seconds of attention/day). For water feedback viewed online, the frequency with which the information is examined will drop dramatically but a user's attention will be more focused—still, online feedback would probably be examined with similar amounts of time to the bill (less than 5 minutes a month). The key is for the feedback system to do the heavy lifting/cognitive effort and make it easy to understand where an occupant can conserve and why.

Finally, it is important to note that water usage is a socially and culturally embedded practice and, as such, will have friction to change. In addition, not all water usage in the home is for *personal* usage—some, such as laundry and dish washing, is for the benefit of the household. Thus, eco-feedback systems may need to take this issue into account.

6.4.1 Limitations

As noted in our study methods section, our recruitment approach led to a sample of respondents who had a high proportion of graduate or postgraduate degrees, science and/or research professions, and positive environmental leanings. At the very least, then, our findings are relevant to highly educated, technical professionals with an interest in water and the environment. However, in some ways, this makes our survey results even more surprising. Our respondent pool had an admitted strong interest in water conservation and the environment but still had extremely limited water knowledge—most struggled to identify major water using fixtures in the home and could not accurately estimate the amount of water used by common, everyday activities such as showering and bathing. More research is necessary to explore these same issues with other populations and in other cultures and countries.

6.5 CHAPTER SUMMARY

In summary, this chapter has shown a lack of knowledge and water literacy around common water usage activities in the home, even among highly educated and environmentally concerned individuals. This gap in knowledge points to the potential of water-based eco-feedback systems to inform, educate and potentially promote more water-efficient usage behaviors in the home. To create effective eco-feedback systems for water, we first turn towards a new type of water sensing system called HydroSense that can monitor water usage at the fixture level (Chapters 7 and 8). In Chapter 9, we combine findings from this chapter and the sensing results from Chapters 7 and 8 to present a number of eco-feedback visualization designs for disaggregated water usage data.

Chapter 7

HydroSense: Pressure-Based Sensing to Identify Water Usage Events in the Home

This chapter presents HydroSense, a low-cost and easy-to-install solution for sensing water usage from a single installation point. HydroSense is based on the continuous analysis of *pressure* within a home's water infrastructure. When a water fixture is opened or closed, its valve generates a unique pressure wave that propagates throughout the plumbing system. HydroSense observes these pressure transients and classifies them into fixture usage events (*e.g.,* the upstairs bathroom toilet was just flushed). HydroSense also provides estimates of the *amount of water being used* at each fixture based on the magnitude of the resulting *pressure drop* within the water infrastructure during water usage events.

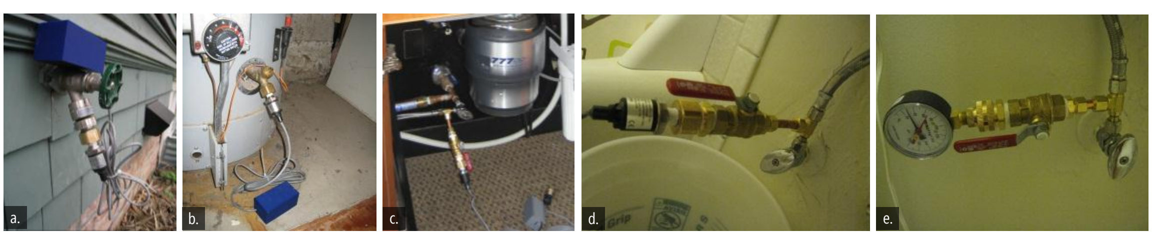


Figure 7.1: HydroSense is a pressure-based sensing solution that disaggregates water usage at the fixture level from a *single* installation point. HydroSense uses a digital pressure sensor that can be installed onto (a) an exterior hose bib or (b) water heater drain valve in the same way that one would attach a garden hose. If these installation points are not available, HydroSense can also be installed at the 3/8" hose connection points of toilets (not shown), (c) kitchen sinks or (d) bathroom sinks. (e) An analog pressure gauge shown for comparison.

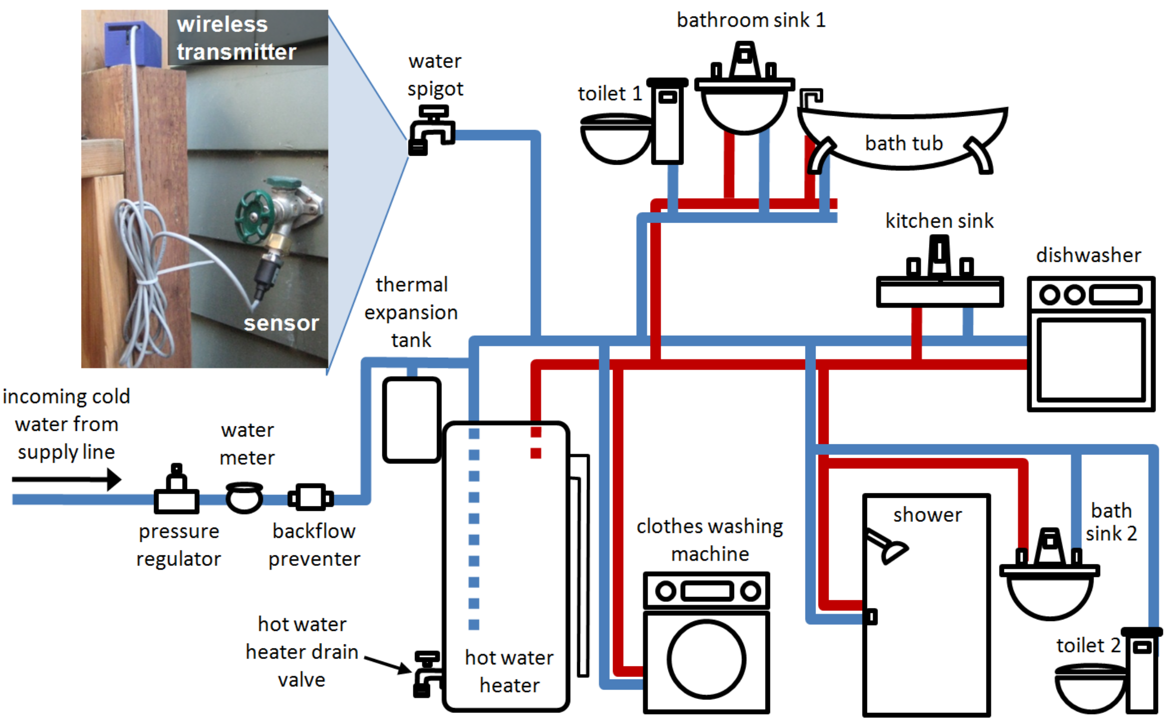


Figure 7.2: An illustrative schematic of a basic plumbing layout in a two-bathroom home. HydroSense can be easily installed at any accessible location in a home's water infrastructure, with typical installations at an exterior hose bib (shown above), a utility sink spigot, or a water heater drain valve. By continuously sensing water *pressure* at this single installation point, HydroSense can both *identify individual fixtures* at which water is being used as well as estimate the *amount of water being used*.

This work represents a significant advance over prior research in several regards:

First, HydroSense can be *easily installed* at any accessible location within a home's existing water infrastructure. Typical installations will be at an exterior hose bib, utility sink spigot, or water heater drain valve (Figure 7.1 and Figure 7.2). If unavailable or not easily accessed (*e.g.,* in an apartment unit), HydroSense can also be installed at the water connection point for a dishwasher, clothes washer, or toilet. All of these are simple screw-on installation points, with no need for a plumber.

Second, HydroSense's analysis of *pressure* provides the unique capability of sensing both the *individual fixture* at which water is currently being used as well as an estimate of the *amount of water being used*. HydroSense is the first practical approach to enabling applications that require both. Our sensing of pressure is also less susceptible to ambient noise, as has been encountered in previous microphone-based infrastructure-mediated systems.

Third, we evaluate HydroSense in ten very diverse homes, thus providing a more *robust evaluation* than any previous work on water-related home activity sensing. We demonstrate reliable

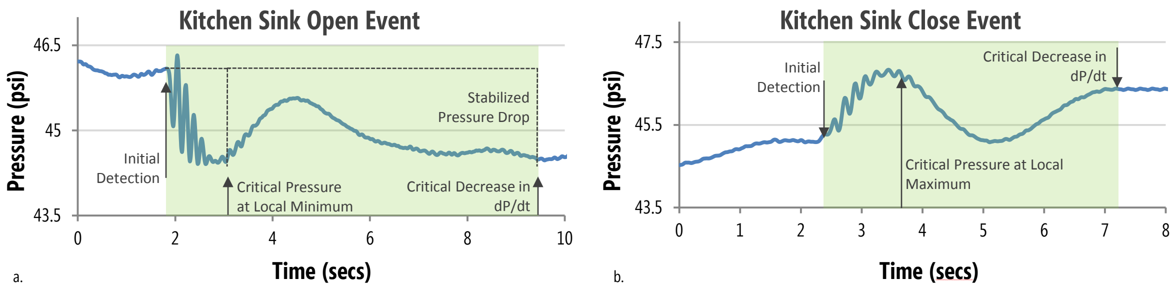


Figure 7.3: HydroSense identifies the unique pressure waves generated when fixtures are (a) opened or (b) closed. These waves propagate throughout a home's plumbing infrastructure, thus enabling the single-point sensing approach. The two pressure waves shown in the figure are from kitchen sink open and close events. Our algorithm identifies that an event is occurring, segments the event (indicated by the green highlight) and then classifies the event according to its shape.

segmentation of valve pressure *events* from the surrounding sensor stream, show reliable classification of *valve open* and *valve close* events, show the successful identification of *individual fixtures* with 96% aggregate accuracy, and show that an appropriately located and calibrated system can estimate water usage with error rates comparable to empirical studies of traditional utility-supplied water meters. In addition, we present initial forward-looking analyses of compound event detection, a comparison of sensing at different locations, and a first look at the temporal stability of pressure event signatures. Our evaluation both validates the feasibility of our approach and provides a basis for future analyses and improvements.

Figure 7.2 illustrates a typical plumbing arrangement in a two-bathroom home (discussed in greater detail in the next section). Figure 7.3 shows an annotated signal captured by our sensor. The signal is a kitchen faucet fixture being turned on, captured by our sensor at an exterior water bib. The remainder of this chapter first discusses the theory behind our approach, presents our sensor implementation, and summarizes our in-home data collections. We then present our analyses of individual fixture identification and water flow estimation, follow by a discussion of some important directions for future work.

7.1 BACKGROUND AND THEORY OF OPERATION

In this section, we provide background on residential water supply systems and in-home plumbing. We also introduce the basic theory of operation that motivates our approach.

Households obtain water from one of two sources: a public water supply or a private well. Public water is distributed by local utilities, relying on gravity and pumping stations to push water through major distribution pipes. Residences are connected to a water main by a smaller service line, where the water meter is typically found. A backflow valve accompanying the water meter prevents household water from flowing back into the main. Homes with private wells use a pump to draw the water out of the ground and into a small tank within the home. A pressure bladder pushes water from the tank when a valve in the home is opened. Private wells are typically unmetered.

Figure 7.2 depicts a typical in-home plumbing system. Cold water enters through the service line, typically at 50-100 pounds per square inch (psi[34]) depending on such factors as the elevation and proximity to a reservoir or pumping station. Many homes have a pressure regulator that protects the home from transients (or pressure spikes) from the main and also reduces the incoming water pressure to a level safe for household fixtures.

After the regulator, there are two basic layouts found in typical residential piping, *series plumbed* and *branched*. Almost all multi-fixture homes have a combination. The cold water supply branches to the individual water fixtures (*e.g.,* toilets, sinks, and showers) and into the water heater. A traditional water heater heats water in an insulated tank using electric coils or gas. When hot water is used, the pressure from the cold water supply line pushes hot water out of the tank and refills it with cold water. The cold water feed line stretches down to the bottom of the tank. Cold water remains at the bottom until it is heated (as cold water is denser than hot water) and the hot water line draws from the top of the tank. Every hot water tank has a pressure relief valve and a drain valve, which is important for maintenance as water heaters should be drained at least once a year to flush mineral deposits and increase operating efficiency. Many homes also have a thermal expansion tank connected to the water heater, providing space to store excess water as it expands during heating. Some homes instead use tankless heaters, which provide hot water on demand by circulating it through burners or electric coils. Both approaches connect cold and hot pipes of a home’s plumbing system. The pressure waves leveraged in our approach travel through this connection, enabling the HydroSense unit to detect both hot and cold water activity with a single sensor.

In summary, the plumbing system forms a closed loop pressure system, with water held at a stable pressure throughout the piping when no water is flowing. Homes with a pressure regulator have stable pressure unless the supply pressure drops below the regulator’s set point. Homes without a regulator may experience occasional minor changes in water pressure depending on neighborhood water demand.

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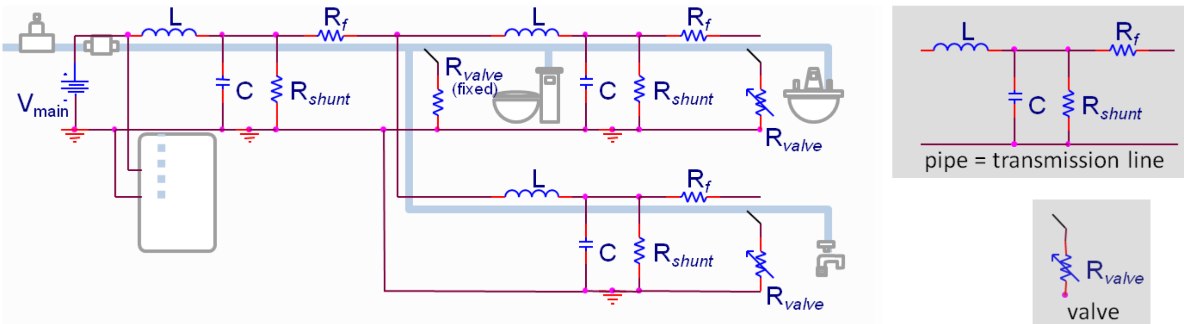
[34] 1 psi ≈ 68.95 mbar



a. b.

Figure 7.4: (a) The transmission line equivalent network for a common bathroom fixture configuration. Only cold water is shown. In this analogy, pressure is analogous to voltage, water flow to electrical current, and the water valve and water pipe as shown in (b).

For explanatory purposes, it is, perhaps useful to draw an analogy between a household water pipe network and its electrical equivalent (Figure 7.4). Water pressure is analogous to voltage, water flow to electrical current, and water valves to electrical switches with variable resistance. For example, water pressure regulated down to a constant 45 psi is analogous to a 45V DC voltage supply. Just as water flow occurs in the direction of higher pressure to a lower pressure, so does current flow from a higher voltage to a lower voltage: the greater the difference, the greater the flow. When an electrical switch is thrown, the value of the resistance controls the amount of current that escapes to ground (*i.e.,* the same way that the size and amount that a valve is open controls the amount of water flow to a drain). In a simplified form, a water pipe is analogous to an electrical transmission line with an inductor and a capacitor (Figure 7.4b). In this way, the network of water pipes in a home can be modeled as a collection of electrical transmission lines (*i.e.,* a linear system with a transfer function given by the interconnection and length of pipes). Although we continue to use some electrical analogies throughout the chapter, they serve only as an additional supplement to our explanations and are not necessary to fully understand the principles upon which HydroSense operates.

7.2 IDENTIFYING AND ESTIMATING WATER USE AT THE FIXTURE LEVEL

The instant a valve is opened or closed in a water fixture, a pressure change occurs and a *pressure wave* is generated in the plumbing system (Figure 7.3 and Figure 7.10). Transient pressure wave phenomenon results from the rapid change of water velocity in a pipeline. For example, when a running faucet is turned off, the valve closure abruptly stops the water flow. Flowing water in a pipe, however, has momentum and is compressible. So, rather than stopping outright, the momentum compresses a finite volume of water against the closed valve, which results in a buildup of pressure at the valve head. Once this buildup reaches a critical point, the pressure at the valve head starts to decompress and the water flow is reversed until it reaches the backflow prevention valve of the house, where the cycle repeats. In the electrical analogy, this is analogous to the cyclic oscillation of charge and flow between inductors and capacitors in transmission lines.

The water pressure wave phenomenon is often referred to as a *surge* or *water hammer* and can create a loud hammering noise as the wave travels through pipes. The magnitude of the surge is dependent upon the operating pressure of the home and the flow of water through the valve. The water hammer transient can have a positive or negative rate of change depending on whether a valve is being opened or closed. Appliances such as dishwashers or clothes washers control their valves mechanically and thus often create the most pronounced water hammer. An abrupt change in flow can create dangerously high pressure transients that exceed safe operating limits for residential pipes. A thermal expansion tank and water hammer arresters offer partial dampening of these transients. Without arrestors, the flow decreases so quickly that the resulting pressure wave can burst the pipe (like the arc voltage produced by opening a switch near an inductor). However, most valve openings/closings manifest as water hammer transients that are harmless but can be detected by a pressure sensor installed on the plumbing system. Water hammer typically lasts several seconds as the pressure wave oscillates back and forth through the pipes. We can detect this water hammer effect *anywhere* along the plumbing infrastructure (even with dampeners installed), thus enabling the single-point sensing approach.

The *unique* transient or water hammer signature that we sense for a particular fixture depends on three factors: the *valve type,* the valve's *location* in the home pipe network, and, to a lesser extent, the way in which the valve is opened or closed. Intuitively, you can think of each valve exciting the plumbing system differently along different points in its infrastructure, much like blowing a harmonica at different points produces different sounds. The physical reasons why these factors produce a unique transient, on the other hand, is best explained using the electrical analogy. The *valve type* controls the resistance of the analogous electrical switch. When the switch is closed, a low resistance path to ground is created suddenly generating an *impulse* which excites the network. Valves with lower resistances allow more water flow and create impulses with greater magnitude. The *valve location* changes where the impulse is applied. When the same impulse is applied in a different location, the path back to the sensor goes through a different set of transmission lines, altering the transfer function from the valve to the sensor and, thus, changing the shape of the transient. Moreover, each transmission line has a unique resonance that is excited by the impulse. For example, in Figure 7.3 it is easy to see two resonant frequencies in each transient, the lower frequency resonance results from a long length of pipe (which excites a larger wavelength) and the high frequency resonance from a shorter pipe length. This point provides great discriminative power allowing us to distinguish between two fixtures of the exact same model such as the same toilet located in two different bathrooms of a home because each pressure wave traverses a different path before reaching the sensor. We have even observed that the pressure transient generated between two cold sink valves located in the same bathroom (such as those found in a "his and her" bathroom sink setup) have unique transients even though there is only a small additional length of pipe between them.

Finally, for manually operated valves, the way the valve is operated can affect the impulse applied to the system in two ways: the *speed* at which the valve is opened affects the slope of the excitatory impulse and the *flow rate* the valve opens to affects the magnitude of the impulse. As the speed of the valve opening becomes slower, the input excitation is not modeled well by an impulse, and instead is better modeled by a ramp function. In practice, slowly opened valves are rare occurrences, but opening a valve to different flow rates is quite common (*e.g.,* opening a bathroom sink cold valve full stop to fill a cleaning bucket vs. opening the cold valve partially to wet a toothbrush). As the magnitude of the impulse becomes smaller, the amplitude of the resonances excited in each transmission line also becomes smaller, but the resonant frequency does not change. The relationship between impulse magnitude and resonance amplitude is non-linear and system dependent. Transmission lines close to the switch are affected less than lines farther away. The algorithm outlined in this chapter does not address this issue directly, but we return to this phenomenon in the discussion section.

Changes in pressure and the rate of transient onset allow us to accurately detect and identify the source of valve open and valve close events. They also allow us to estimate flow. This stems directly from our electrical analogy, where knowing the resistance and the change in voltage (*i.e.,* pressure) allows one to determine the current (*i.e.,* flow). Unlike current, however, water flow comes in two forms: laminar and turbulent, which affects the relationship between pressure and flow.

Laminar flow is characterized by the movement of fluid particles parallel to each other, with no transverse movement or mixing. In contrast, turbulent flow is characterized by vigorous intermixing within the flow field resulting in small, random fluctuations in flow. Physically, the two flow states are linked in that any laminar flow can become turbulent with a change in fluid velocity—think of the water flowing out of a typical bathroom faucet: when the faucet is opened partway, water flows in a clear, solid-looking stream and does not splash; however, when the faucet is opened all the way, the water flow turns more opaque, bubbly and chaotic.

The conditions under which liquids transition from laminar to turbulent flow are characterized by a dimensionless value known as the Reynolds number (Reynolds, 1883), which is dependent on the kinematic viscosity *v* of the fluid, the volumetric flow rate of the fluid in a pipe *Q,* and the radius of the pipe *r*:

$$R_e = Q\frac{2\,r}{\upsilon} \tag{7.1}$$

It is generally accepted that a Reynolds number less than 2,300 results in laminar flow and greater than 4,000 result in turbulent flow. In between there is transition between both (Reynolds, 1883). Using the most common flow rates for residential water fixtures, it is possible to calculate the Reynolds numbers for a typical home. The Reynolds numbers for water flow in a typical home are in the range of 1,000-50,000 for 3/8" diameter pipe segments and in the range of 400-22,000 inside the 1" diameter supply lines—which means fluid flow in a home can be laminar, turbulent, or a mix of both. We will address the laminar flow condition first, showing that the relationship between pressure drop and flow is linear. We then show that the nonlinearity induced by turbulent flow can be sufficiently modeled as linear, with minimal loss of accuracy.

7.2.1 Laminar Flow

When laminar, water flow is directly proportional to the pressure drop sensed at the HydroSense unit. Poiseuille's Law offers a precise definition of this relationship: when the flow through a pipe is laminar, the volumetric flow rate of fluid in a pipe *Q* is dependent on the radius of the pipe *r*, the length of the pipe *L,* the viscosity of the fluid *μ* and the pressure drop Δ*P* from the start and end of the pipe length:

$$Q = \frac{\Delta P\,\pi\,r^4}{8\,\mu\,L} \tag{7.2}$$

Note how increasing pipe length reduces flow (by creating more resistance) and increasing the pipe radius pipe increases flow. Pipe length has a linear relationship with flow; if you double the pipe length, the flow is halved. If, instead, you halve the pipe diameter, flow is reduced by a factor of sixteen. Poiseuille's law can be simplified by the fluid resistance formulation, which states that the resistance of flow is proportional to the drop in pressure divided by the volumetric flow rate.

$$R_f = \frac{\Delta P}{Q} \equiv \frac{8\,\mu\,L}{\pi\,r^4} \tag{7.3}$$

Thus, we can use fluid resistance to abstract some of the variable complexity from Poiseuille's law, resulting in:

$$Q = \frac{\Delta P}{R_f} \tag{7.4}$$

This is analogous to Ohm's law (I = V / R). HydroSense measures the change in pressure *ΔP* from the pressure regulator to the sensor. In order to compute *Q*, we must estimate the remaining unknown R_f . R_f is bounded by two factors: (1) water viscosity, which can easily be calculated according to temperature and (2) the radius of residential pipes, which are either 1/4" or 3/8" in diameter (1" for supply lines in an apartment). This leaves *L*, the length of the pipe, as the main unknown. *L* will change depending on the water fixture being used, as each path from intake to fixture is different.

7.2.2 Turbulent Flow

When the flow of water through the pipes is turbulent instead of laminar, Poiseuille's law does not directly apply. Turbulent flow results in a non-linear relationship between pressure and flow. Instead of pressure being proportional to flow, the relationship becomes such that *P* is proportional to $Q^{1.75}$. The mixing induced in turbulent flow dissipates the force from the head pressure, requiring that more pressure be exerted to sustain the same flow of water. The relationship between pressure and mean flow can be determined empirically, and is given by:

$$\Delta P = Q^2 \frac{L\,\rho\,0.3164}{4\,r\,\sqrt[4]{R_e}} \tag{7.5}$$

where ρ is the density of the liquid. This is known as the Blasius formula (Blasius, 1911) and is valid for liquid flow with Reynolds numbers less than 100,000. The pressure and flow relationship given by the Blasius formula is plotted in Figure 7.5 (blue). Also shown is the typical operating range for flow in a household and the best fit linearization (black) of the Blasius formula in the most common operating range (top left inset). If we assume laminar flow, the slope of the black line is proportional to the estimated R_f from Poiseuille's law. The actual R_f is proportional to the instantaneous slope of the blue line. The worst case approximation error of R_f is 70% at a flow rate of 10 gpm. However,

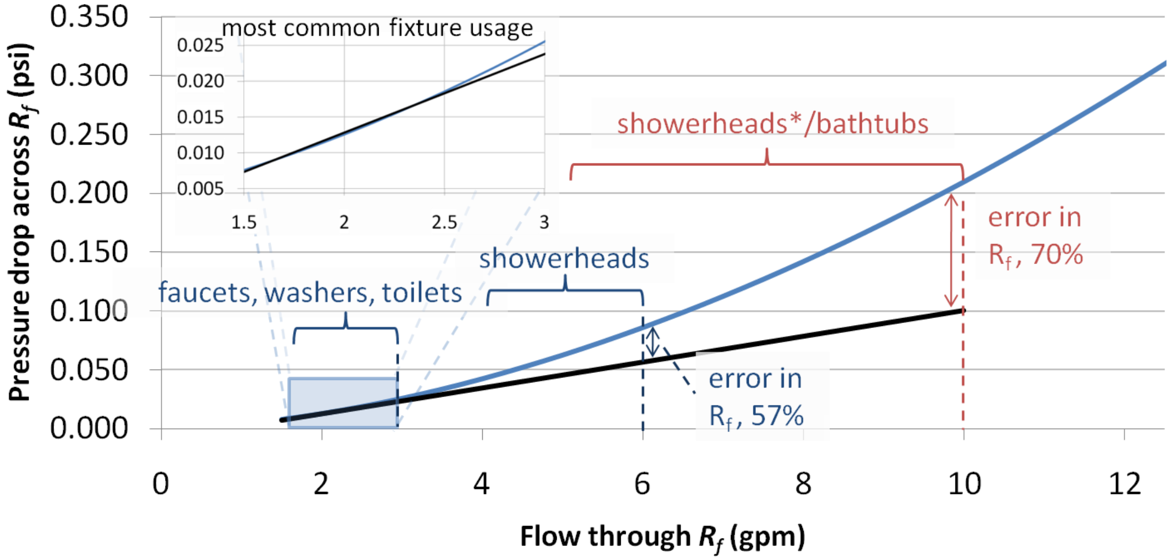


Figure 7.5: The pressure versus flow in a 1" diameter pipe of length 6.5' using the Blasius formula (blue) and the linearization of the equation (black) around the point of most common fixture usage. Also displayed are the most common fixture flow rates. The (*) denotes a fixture built before the 1992 Energy Policy Act, requiring US manufactured fixtures to use less water.

this only results in an error in ΔP of 0.11 psi. Because the pressure drop, ΔP, at the HydroSense unit is the sum of the pressure drop at the valve (on the order of 5-20 psi) and the pressure drop along the pipes (in this example, below 0.11 psi), the resulting error in Q is between 0.5-2.2%. Of course, as the pipe length increases, this error increases. Even still, with a pipe length of 50 ft., the error is still less than 10%. Thus, the linear model *can* be applied with minimal loss of accuracy even when the water flow through the household is turbulent.

7.2.3 Characterizations

We note that these equations are not comprehensive. They do not account for the smoothness of the inner pipe surface, the number of bends, valves, or constrictions in pipes, nor pipe orientation (*e.g.,* the forces of gravity and changes in barometric pressure). While many of these factors can be estimated using home size, type of plumbing (PVC, copper, etc.), and number of fixtures, we have found these effects can be treated as negligible for home pipe networks. We simply estimate R_f for each home by sampling flow rate at strategic locations (varying distances from the supply inlet).

7.3 PROTOTYPE SENSOR DESIGN

Our prototype HydroSense sensor implementation consists of a customized stainless steel pressure sensor, an analog-to-digital converter (ADC) and microcontroller, and a Bluetooth wireless radio (see Figure 7.6). We built two different HydroSense prototypes: one with a pressure range of 0-50 psi and the other 0-100 psi. The higher dynamic range is useful for homes with high supply pressure or without a pressure regulator. The pressure sensor is a P1600 series manufactured by Pace Scientific™. It comes standard with a built-in ¼” NPT male connector, which we fitted with a ¾” brass adaptor and Teflon tape. This allows us to easily install our sensor at any ordinary water spigot or outlet. The sensor has an operating temperature of -40 to 257°F and a pressure response time of less than 0.5 milliseconds. The theoretical maximum sampling rate is therefore 2 kHz, but we found 1 kHz more than sufficient.

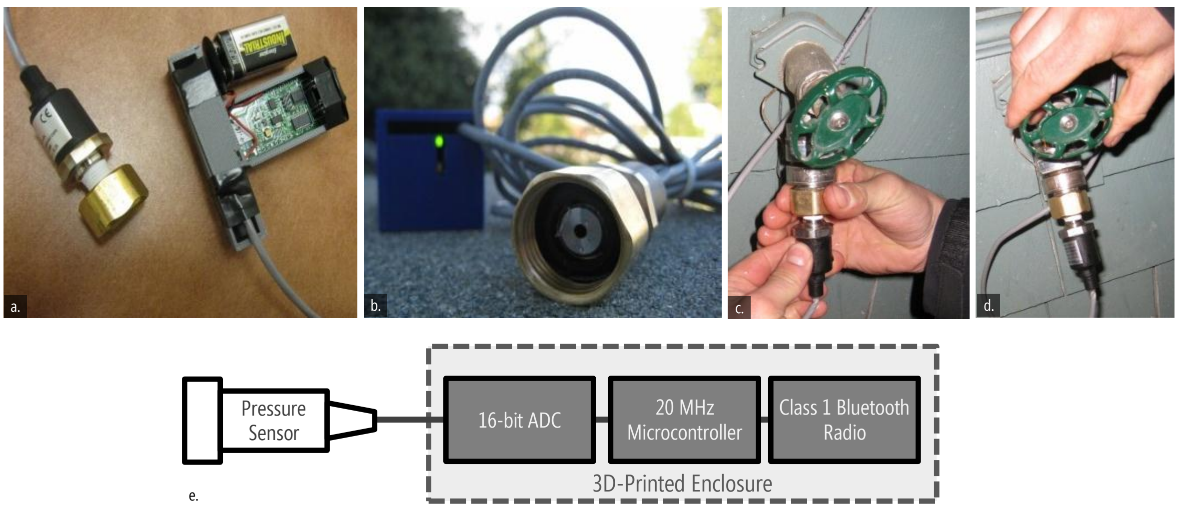


Figure 7.6: (a) An early HydroSense implementation. (b) HydroSense pressure sensor (foreground) with 3D-printedenclosure protecting electronics (background). (c) Installing HydroSense on a ¾” hose spigot. (d) Once screwed on tight, the water valve must be opened to allow the sensor to sense the indoor plumbing pressure. (e) A schematic of HydroSense including the Pace Scientific pressure sensor, the 16-bit Texas Instruments ADS8344 ADC and AVR microcontroller, and the Class 1 Bluetooth radio.

The pressure sensor’s output is ratiometric to the 5 VDC supply voltage (the output voltage is a ratio of the supply). The sensor is connected to a 16-bit Texas Instruments ADS8344 ADC and AVR microcontroller, with a resolution of approximately 0.001 psi for the 50 psi sensor and 0.002 psi for the 100 psi sensor. The microcontroller is connected to a Class 1 Bluetooth radio implementing the serial port profile. It can reliably sample and stream pressure data over the Bluetooth channel. We use a 5V low-drop power regulator and the entire unit operates on a single 9V battery.

The pressure sensor has a mechanical shock rating of over 100g, making it insensitive to pipe vibration occasionally caused by some water hammer events. Although the pressure sensor comes calibrated and tested for linearity from the factory, we confirmed the output of our entire sensor system using known pressure loads. Ten samples were taken with our sensor connected to a pressure-regulated water compressor. All measurements were well within the pressure sensor's tolerance of 0.25% at 25° C. The entire unit is weatherproof and can be installed in damp locations.

Our current implementation does not offer a pass-through solution (*i.e.,* allowing the installation fixture to be used as normal), but this modification is trivial.

7.4 PILOT TESTING

Before installing HydroSense into homes to collect data for our classification experiments, we created a test harness to test our HydroSense hardware and data logger software as well as to perform some preliminary experiments in a controlled fashion (Figure 7.7). The test harness includes a pressure regulator, a GPI TM Series inline electronic water meter (1/2”), five valves, one detachable faucet outlet, and roughly 20 feet of pipe with a branch. The test harness is also reconfigurable to experiment with different branching and pipe length setups (Figure 7.7a and b).

In our preliminary experiments using the test harness we validated the flow rate equations from the previous section, fleshed out bugs with our hardware and data logger, and informally tested how different pipe configurations shaped the resulting pressure transients.

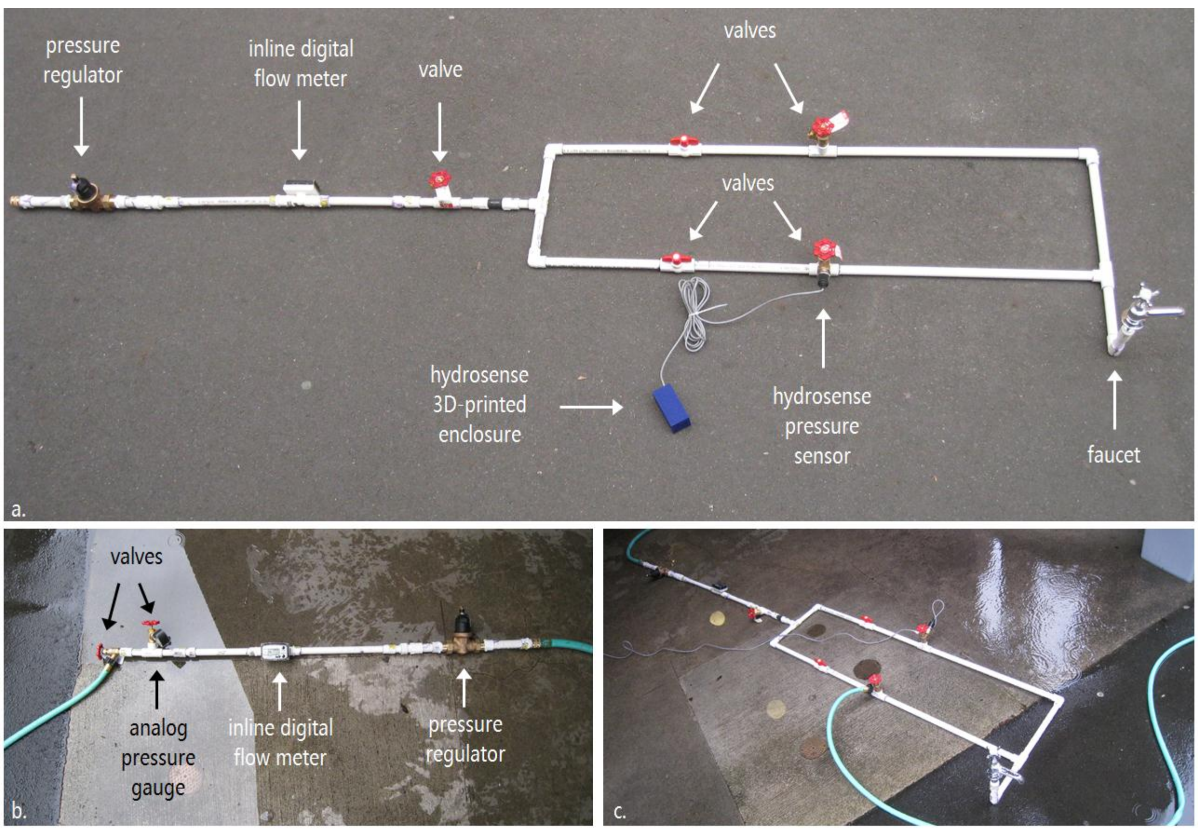


Figure 7.7: The HydroSense test harness created to empirically test our hardware and explore flow calculation algorithms in a controlled fashion. (a) The full test harness. (b) A reconfigured (short) version of test harness. (c) Using the test harness for preliminary experiments.

7.5 IN-HOME DATA COLLECTION

Once we had completed pilot testing HydroSense in a laboratory environment, the next step was to collect data in real homes and test and iterate on our classification algorithms. To validate our general approach, our sensor implementation, and our algorithms, we collected labeled data in four cities using ten homes of varying style, age, and diversity of plumbing systems (see Table 7.1:). Homes H1-H9 used metered water from the public utility, whereas home H10 used a private well.

ID / Water Supply	Style / Built / Remodel	Size / Floors / Fixtures	Exp. Tank/ Regulator / Recirc. Pump	Water Heater / Plumbing/ Static PSI	Sensor Install Point
H1 **Public Utility**	Single-Family 2002	3200 sqft 2 flr + bas 12 fixture	Yes Yes No	Tank PVC 46 psi	Hose Bib
H2 **Public Utility**	Multi-Family 1909/96	2160 sqft 2 flr + bas 5 fixtures	No No No	Tankless Copper 46 psi	Hose Bib
H3 **Public Utility**	Single-Family 2003	4000 sqft 2 flr + bas 6 fixtures	Yes Yes No	Tank Copper 41 psi	Hose Bib
H4 **Public Utility**	Single-Family 1921	1630 sqft 1 flr + bas 4 fixtures	No No No	Tank Galvan. 43 psi	Hose Bib
H5 **Public Utility**	Single-Family 1913	2000 sqft 2 flr + bas 5 fixtures	No No No	Tank Copper 55 psi	Hose Bib
H6 **Public Utility**	Single-Family 1974/85	3100 sqft 2 flr 8 fixtures	Yes Yes Yes	Tank Galvan. 46 psi	Hose Bib
H7 **Public Utility**	Apartment 1927	746 sqft 1 flr 5 fixtures	No Yes No	Tank Copper+Galvan 33 psi	Water Heater
H8 **Public Utility**	Single-Family 1922 / 2006	3650 sqft 2 flr + bas 3 fixtures	Yes Yes Yes	Tank Copper 75 psi	Utility Sink Faucet
H9 **Public Utility**	Single-Family 1904 / 95 est.	1790 sqft 2 flr + bas 4 fixtures	No No No	Tank Copper 72 psi	Hose Bib + Water Heater
H10 **Private Well**	Resort Cabin 1950/80	900 sqft 1 flr 4 fixtures	No No No	Tank Galvan. 65 psi	Hose Bib

Table 7.1: A summary of the homes in which we collected data, including the style, size (1 sqft ≈ .093 sqm), age of the home, how many fixtures we tested, characteristics of the plumbing system, and where we installed our sensor.

For each home, we first measured the baseline static water pressure and then installed the appropriate HydroSense unit (0-50 or 0-100 psi) on an available water hose bib, utility sink faucet, or water heater drain valve. Each collection session was conducted by a pair of researchers: one would record the sensed pressure signatures to a laptop while the other activated the home's water valves

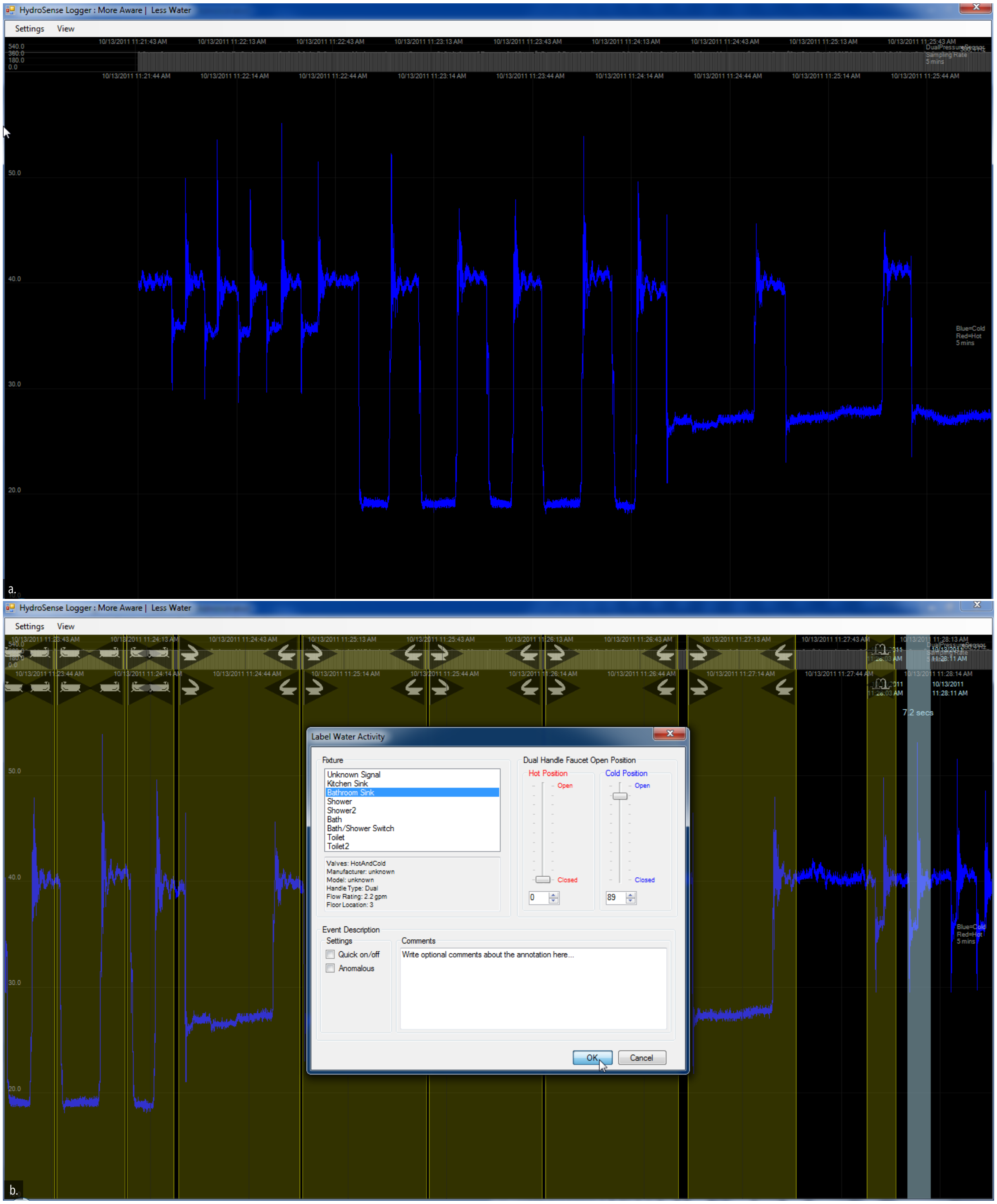


Figure 7.8: The HydroSense Logger tool was used to collect staged water usage event pressure stream data that were manually annotated with ground truth labels. (a) Five bathroom sink on/off water usage events followed by five bath on/off water usage events, and 3 toilet flushing events. (b) Parts of the pressure stream could be selected and annotated. The yellow time-series highlights show the boundaries of labeled events (the icons at the top correspond to the type of water usage event). The light blue highlight at the far right is the pressure wave currently selected for annotation in the modal dialog box.

(Figure 7.8 and Figure 7.9). The pressure signatures were recorded using a graphical logging tool, which also provided real-time feedback of the pressure data via a scrolling time-series line graph. We conducted five trials per valve on each fixture (*e.g.,* five trials for hot water and five trials for cold water; see Figure 7.8). For each trial, a valve was opened completely for at least five seconds and then closed. For the toilet trials, the toilet flush and full fill cycle were logged. Note that for the faucet experiments, we did not collect data on partially opened valves nor the speed with which they were opened. We return to this issue in the discussion section.

In four of the ten houses (H1, H4, H5, and H7), we also collected flow rate information for the faucet (kitchen and bathroom) and shower fixtures. In addition to logging sensed pressure, we measured the amount of time it took to fill a calibrated bucket to one gallon (a method preferred by water utilities for accurately measuring flow). This was repeated for five trials for each valve—see Figure 7.9c.

In total, our in-home data collection yielded 775 fixture trials and 155 flow rate trials across 76 valves and 51 fixtures.

Figure 7.9: Collecting controlled experimental water usage trial data using the HydroSense Logger tool visible in (a) and (b). In (c), collecting flow rate data in addition to logging sensed pressure.

7.6 ALGORITHMS FOR CLASSIFYING WATER USAGE EVENTS

Given our collected data, we now pursue a three-step approach to examine the feasibility of identifying individual fixture and individual valve events according to the unique transient pressure waves that propagate to our sensor. Recall that each valve event corresponds to a pressure wave when a valve is either opened or closed. We first segment each individual valve event from the stream, identifying its beginning and end to enable further analysis. We then classify each valve event as either a valve open or a valve close event. Finally, we classify the valve event at two levels of granularity: (1) according to the individual fixture that generated it (*e.g.,* bathroom sink vs.

kitchen sink) and (2) according to the individual valve that generated it (*e.g.,* kitchen sink cold water vs. kitchen sink hot water).

7.6.1 Transient Event Segmentation

Before analyzing the characteristics of a valve event, we first segment it (*i.e.,* isolate it) from the surrounding sensor stream. Segmentation must be effective for many different types of events, and so it is important to consider only features that are likely to be most typical of all valve events. Our approach is illustrated in Figure 7.10. The raw signal is smoothed using two low-pass linear phase finite impulse response filters with different cutoff frequencies (1 Hz and 13 Hz, black and blue lines in Figure 7.10, respectively). Almost all the spectral energy is below 10 Hz. Thus the 13 Hz filter captures a de-noised version of the transient. Below 1 Hz the relative *decrease* or *increase* in pressure is more apparent which aids in classifying the transient as a valve open or valve close event. The derivative of the filter is also calculated using a windowed ideal differentiator filter with a cutoff of 2 Hz (*i.e.,* the optimal differentiator in terms of squared error). The smoothed signal and its derivative are then analyzed in a sliding window of 1000 samples (one second of sensed pressure).

The beginning of a valve event corresponds to one of two conditions. The most common is when the derivative of the smoothed signal exceeds a specified threshold relative to static pressure, indicating a rapid change. For H1 (static pressure of 45 psi), this value was found empirically to be approximately 2 psi/sec. For generalizing to other homes, this value was scaled by the home's actual static pressure. The less common second condition is when the difference between the maximum and minimum pressure values in the sliding window exceeds a threshold relative to static pressure, indicating a slow but substantial change (approximately 1 psi for a home with 45 psi static pressure, scaled by the actual static pressure).

Each transient represents a damped sinusoid. After the beginning of a valve event is detected, the next change in the sign of the derivative represents the time at which the extreme value of the pressure transient occurs (which may be a maximum or a minimum). This extreme value is used to assist in the calculation of the end of the transient. The end of a segmented valve event is typically detected as the first point at which an extreme of a fluctuation (a change in the sign of the derivative, dP/dt) is less than 5% of the magnitude of the first extreme following the beginning of the event. It is also possible for an event to be ended by a rapid increase in the magnitude of fluctuation. This corresponds to the occurrence of a compound event, as we will discuss in greater detail in a later section.

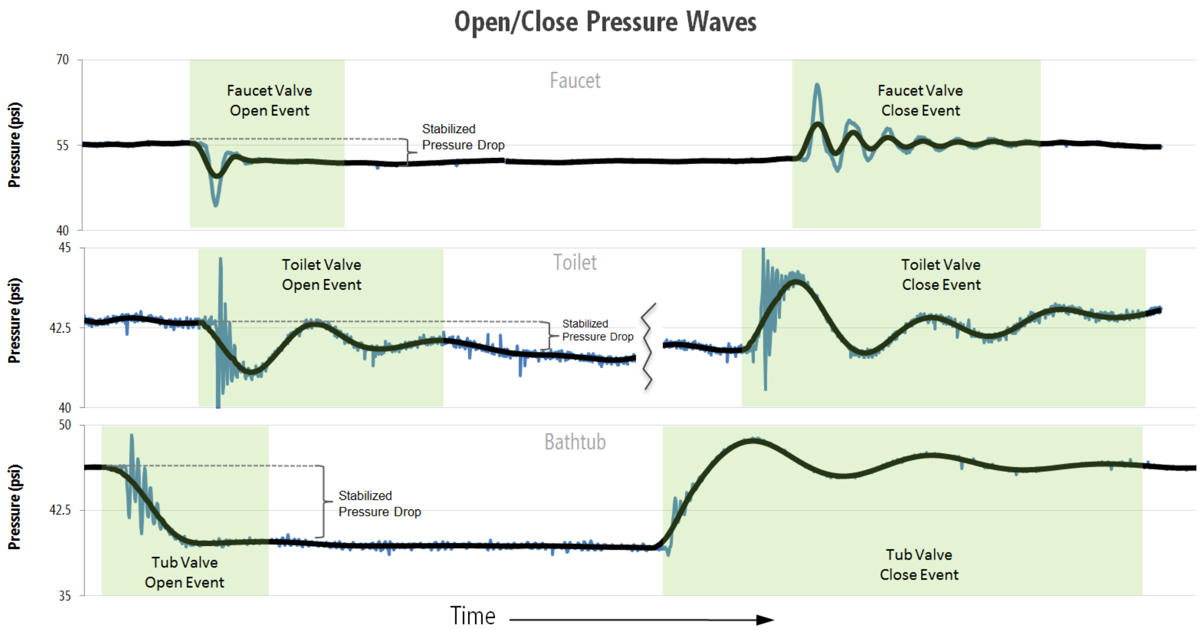


Figure 7.10: Several sensor pressure streams from our in-home data collections. Each stream corresponds to a water valve being opened, remaining open for some amount of time, and then closed. Both raw pressure (shaded blue lines) and filtered pressure (black) are shown. We separately segment the valve open and valve close events from the sensor stream, as indicated by the highlighted regions of the streams. We estimate water flow to the valve based on the stabilized pressure drop while the valve remains open (the difference in pressure before the valve opens versus after it).

Applying this method to our collected in-home data yielded appropriate segmentations of 100% of our valve events from their surrounding sensor stream. Additionally, this method was effective at finding leaky flapper valves in toilets. After our initial data collection, we noticed that this method segmented multiple valve closings when a particular toilet in H2 was flushed. Further inspection revealed that the flapper valve of the toilet was loose, resulting in two concurrent valve closings.

7.6.2 Classifying Transient Waveform as an Open or Close Event

After segmenting each valve event, we classify it as either a *valve open* or a *valve close* event. We apply a classifier that first considers the difference in the 1 Hz smoothed pressure at the beginning and the end of the segmented event. If the magnitude of this difference exceeds a threshold (approximately 2 psi for a home with 45 psi static pressure, scaled by the actual static pressure), the event can be immediately classified (a pressure decrease corresponds to a *valve open* and a pressure increase to a *valve close*). Otherwise, the event is classified according to the average value of the derivative between its beginning and its first extreme. A *valve open* creates an initial pressure decrease (a negative average derivative), while *valve close* events create an initial pressure increase (a positive average derivative). Figure 7.3 and Figure 7.10 illustrate this observation.

Applying this method to the segmented valve events from our collected in-home data yields 100% correct classification of valve open and valve close events. We note that this method and our event segmentation method described above require only knowledge of the static pressure in the home, which can be easily and automatically derived. HydroSense can thus be used immediately and without supervision to detect fixture openings and closings in a home. Fixture- and valve- level classification, however, require a supervised calibration process.

7.6.3 Valve- and Fixture-Level Classification

The final step in our three-step approach is to identify the valve and fixture source of the segmented open and close events. Here, we use a template matching approach. Before going into our analysis in detail, it is worth discussing the ways in which water is used in the home that can impact classification. First, note that valves can be divided into two groups: automatically (or electro-mechanically) controlled valves such as those found in dishwashers, laundry machines, and ice makers, and manually controlled (or human operated) valves such as those found in kitchen sink faucets, bathroom sink faucets, showers, and tubs. Toilets are a hybrid between manually and mechanically controlled valves. Manually operated valves can produce slightly different transients depending on the speed and flow rate at which they are operated, while mechanical valves produce a more distinct transient at a single flow rate. Our database of events contains both mechanically and manually operated fixtures, but our data collection did not explicitly control for different usages of hand operated valves. We address this limitation further in the discussion section.

Our classification approach, template matching, assumes that the transient (*i.e.,* the template) for a specific fixture or valve stays relatively constant between different trials. In Chapter 8, we instead use a probabilistic-based classification approach, which we found to be more robust to signal distortion from compound events and differences in transients due to differences in the manual operation of valves. We have also experimented with using Hidden Markov Models (see Larson *et al.*, 2010).

Note that our template classifier relies solely on the pressure signal for input. Although incorporating contextual factors such as time of day and fixture usage duration would likely boost classification accuracies, these factors are irrelevant in our dataset because our data was collected under controlled experimental conditions. In Chapter 8, we include such factors in our probabilistic approach.

We return now to the details of the template classifier. When supplied with an unknown open or close event from the preceding step, we first filter potential templates according to four complementary distance metrics:

The first distance metric we use is a *matched filter* (North, 1963). Very common in signal detection theory, the matched filter is the optimal detection mechanism in the presence of additive white noise. Its primary limitation is that the signals we want to differentiate are not orthogonal. It is possible to make the signals orthogonal (*e.g.,* using principal component analysis: Pearson, 1901), but we found this type of analysis to be unnecessary. Instead, we transform the data into more orthogonal spaces.

Our second distance metric is a *matched derivative filter*. We include this because the derivatives of our events always resemble exponentially decreasing sinusoids. It is therefore reasonable to believe the derivatives are more orthogonal than the original pressure signals, and that this filter might provide value distinct from the above filter.

The third distance metric is based on the *real Cepstrum*, which is the inverse Fourier transform of the natural log of the magnitude of an event's Fourier transform. This approach attempts to approximate the original version of a signal that has been run through an unknown filter (the valve event we are trying to classify has been transformed by propagation through an unknown path in a home's water pipes). It can be shown that, for linear systems, the lower coefficients of the Cepstrum result largely from the transfer function (an event's propagation through a home's pipes) and the higher coefficients largely from the source (the original impulse at the valve) (Oppenheim and Schafer, 2004). We are interested primarily in the transfer function (in part because it allows differentiating among multiple instances of identical fixtures in a home), so we truncate our Cepstrum to the lower coefficients. The resulting space is highly orthogonalized (a common property of the Cepstrum), yielding a third effective and complementary matched filter.

Finally, our fourth distance metric is the simple *mean squared error*, computed by truncating the longer of two events.

Similarity thresholds used to filter potential templates based on these distance metrics are learned from training data (filtering templates whose similarity to the unknown event are less than the minimum within-class similarity in the training data). If no template passes all four filters, the unknown event is not classified (an application might ignore the event, prompt a person to label an unrecognized fixture, or consider the possibility that the new event indicates the presence of a leak). If templates corresponding to multiple fixtures pass all filters, we choose among them using a nearest-neighbor classifier defined by the best performing distance metric, the matched derivative filter.

7.7 EVALUATION

In this section, we examine the performance of our water usage event classification algorithms as well as our flow inference algorithms. We investigate valve vs. fixture-level classification accuracies, classification performance on hot water events vs. cold water events, and flow calculations with minimal and full calibration data.

7.7.1 Valve-Level and Fixture-Level Classification

We evaluate *valve-level* classification and *fixture-level* classification using an experimental design selected to demonstrate robustness of learned model parameters across the multiple homes in our collected data. Specifically, we conduct a cross-validation experiment that folds our data according to the home in which it was collected.

For our template based classifier, there are ten trials in the cross-validation, with each trial using data from one home as the test data and data from the other nine homes as the training data. After learning model parameters from the test data (the four similarity filter thresholds), we classify each event in the test home using a leave-one-out method. Each test home event is classified using the other events as templates together with the model parameters learned in training.

Table 7.2 presents the results of this evaluation. In particular, the table shows the identification percentages for classifying each *valve* and *fixture* in a home. The main advantage of *valve-level* identification is that hot and cold water usage can be disambiguated. A kitchen faucet, for example, is a single fixture that has two valves, one for hot water and one for cold. The table shows the accuracy of classification for *open* and *close* events within each home (and thus each test fold of the cross-validation), as well as the aggregate accuracy of classification. Accuracies for H9 are shown for two different installation points of the sensor, hose bib (H9A) and hot water heater (H9B). Because of the fixture types within H1 and H3 (all single handle), we did not perform experiments on more than one valve at any fixtures in these homes (thus the valve results and the fixture results are the same).

Analysis of valve and fixture classification reveals that the template classifiers perform well on H1 through H8 and on H9A. However, performance dropped on H10 and on H9B. The relatively poor performance in identifying valve-level events in H10 was due to noise from the eleven cabins that share the same supply line at the resort. Because the cabin was not separately metered our sensor was picking up water events from a portion of these cabins during data collection. When looking at *fixture-level* performance for H10, the classification accuracies increase markedly. This is an indication that noise in a multi-unit domain (*e.g.,* a duplex, small apartment building) may have more effect on *valve-level* identification than *fixture-level* identification.

		Valve-Level Classification Results			Fixture-Level Classification Results		
Home	**Installation Point**	**Valves Tested**	**Valve Open Identification**	**Valve Close Identification**	**Fixtures Tested**	**Fixture Open Identification**	**Fixture Close Identification**
H1	Hose Bib	12	100.0%	100.0%	12	100.0%	100.0%
H2	Hose Bib	8	96.4%	100.0%	5	96.4%	100.0%
H3	Hose Bib	6	100.0%	100.0%	6	100.0%	100.0%
H4	Hose Bib	5	100.0%	100.0%	3	100.0%	100.0%
H5	Hose Bib	9	100.0%	100.0%	4	100.0%	100.0%
H6	Hose Bib	8	100.0%	97.5%	5	100.0%	97.5%
H7	Hose Bib	8	100.0%	100.0%	5	100.0%	100.0%
H8	Utility Sink	6	100.0%	97.1%	3	100.0%	97.1%
H9A	Hose bib	7	97.1%	97.1%	4	97.1%	97.1%
H9B	Water Heater	7	88.6%	71.4%	4	88.6%	74.3%
H10	Hose Bib	7	75.7%	43.8%	4	94.6%	75.0%
Aggregate		83	96.2%	91.8%	55	98.0%	94.7%
		94.1%			96.3%		

Table 7.2: In a cross-validation test of the robustness of learned models across multiple homes, the template classifier resulted in accuracies above 94% for both valve-level and fixture-level classification granularity.

We note that the valve-level results presented here differ from our *UbiComp 2009* publication (Froehlich *et al.* 2009b), which presented similar analysis on the same dataset. We report 75.7 and 43.8 percent accuracy for H10 whereas the previous reporting was 97.1 and 77.1 for H10. The reason for this is twofold: firstly, the learned model parameters have changed in the cross-validation because a new home (H9B) was added. Secondly, Froehlich *et al.* (2009b) reported results for H10 at the fixture-level, rather than valve-level, a mistake which is remedied here (and corrected in Larson *et al.*, 2010). More work is needed to disambiguate signals in a single-meter multi-unit domain, but these results indicate a single sensor may be sufficient to sense *fixture-level* detail across more than one housing unit on a shared supply line, a somewhat different conclusion than that presented by Froehlich *et al.*

Valve Level Confusability Matrix					
Fixture Type	**Accuracy**	**Confusion**			
Faucet	95.3%	424	6	6	9
Toilet	99.3%	136	0	0	1
Clothes Washer	100.0%	15	0	0	0
Dishwasher	100.0%	6	0	0	0
Tub	100.0%	36	0	0	0
Shower	82.4%	112	0	12	12
Confused for:		**Correct**	**Similar Appliance**	**Hot/Cold**	**Diff. Appliance**

Table 7.3: A different view of the results, showing accuracy of identification of individual valves by fixture type, and confusability of different fixtures.

The poor performance on H9B is largely due to the installation point (on the water heater). Although events are transmitted *through* the water heater, many events are significantly dampened. This dampening suppresses some of the defining characteristics of the transients, making them more similar to one another. This sort of dampening can occur during compound events as well—when one fixture is actively flowing while another is opened or closed. The pressure transient from this event is dampened due to the active water movement in the plumbing system. We explore this effect in more detail in Chapter 8.

To investigate performance further, it is interesting to look at how different valves are confused in each home. Table 7.3 presents a different view on the same data, showing the accuracy of *valve-level* classification for different types of fixtures across homes. Also shown is the number of times a valve is confused according to three categories: (1) the valve is confused for a fixture of the same type, (2) the valve is confused for the hot or cold valve from the same fixture, or (3) the valve is confused for a different type of fixture altogether. Notice that similar appliances are rarely confused for one another (*e.g.,* two different sinks or two different toilets). Instead, the source of confusion comes from the *proximity* of two valves in a home. For instance, the main source of confusion in the table comes from a sink and shower in H9B that are consistently confused with each other. The valves are positioned extremely close to each other and within 10 ft. of the water heater. The valves already have similar characteristics because of their proximity, and the water heater acts like a large low-pass filter, dampening out most of the characteristics that make the pressure waves identifiable. Other sources of confusion in the table are largely due to classification errors in H10. However, there is no pattern to valve confusion in H10, supporting the notion of noise from other cabins being the main culprit.

Valve-Level Classification Split by Hot and Cold Water Activations			
Home	Installation Point	Valve Cold Identification	Valve Hot Identification
H2	Hose Bib	97.3%	100.0%
H4	Hose Bib	100.0%	100.0%
H5	Hose Bib	100.0%	100.0%
H6	Hose Bib	98.3%	100.0%
H7	Hose Bib	100.0%	100.0%
H8	Utility Sink	97.6%	100.0%
H9A	Hose bib	100.0%	93.3%
H9B	Water Heater	75.0%	86.7%
H10	Hose Bib	62.8%	57.7%
Aggregate		94.6%	92.9%

Table 7.4: A different view of valve-level classification separated for hot and cold valves in a home.

Table 7.4 shows the accuracy for classification of hot water valves and cold water valves separately. H1 and H3 are excluded because, as previously mentioned, we did not independently test hot and cold water valves (both homes had only single handle faucets/shower making this particular experiment challenging). No real pattern presents itself from the data. Both hot and cold valves can be classified with similar accuracy. Despite these similarities, we remind the reader that our experimental data collection did not control for the speed at which manually controlled valves were opened, or when multiple valves are running in the household. More examination is needed to investigate what effect, if any, hot vs. cold water mixture has on classification accuracy.

Our overall *valve-level* and *fixture-level* classification across all homes is above 90%, including a number of cases where classification accuracy is 100%. All of these results are equal to or better than prior results by Fogarty *et al.* with microphone-based sensors (2006). Of particular note is our ability to reliably distinguish among different sinks within a home, as Fogarty *et al.* found that their microphone-based sensors did not capture enough information to reliably make this distinction. Our dataset contains only a few instances of clothes washer or dishwater use, in part due to time constraints during data collection and in part because Fogarty *et al.* found these fixtures can be easily recognized by their structured cycles of water usage (an approach that can be combined with ours). However, we note that our approach is independent of the number of fill cycles (important if a dishwasher is sometimes run with a pre-rinse cycle) and allows recognition as soon as these appliances first use water (in contrast to being able to recognize them only after their pattern of fill cycles becomes apparent).

7.7.2 Evaluation of Flow Estimation

As previously discussed, the volumetric flow rate Q is proportional to the change in pressure ΔP divided by a resistance variable R_f ($Q = \Delta P / R_f$). We calculate the change in pressure ΔP by measuring the difference between the pressure at the onset of a detected *valve open* event and the stabilized pressure at the end of the segmented *valve open* pressure wave impulse. The resistance variable R_f cannot be directly measured, so we instead learn it empirically by capturing ground truth flow rate information together with the corresponding change in pressure for each valve. This section considers two scenarios with regard to learning R_f. In the first, we assume a single calibration of flow for every valve of interest. In the second, we attempt to use information from the calibration of some valves to estimate R_f at valves that have not been calibrated. In both scenarios, we assume laminar fluid flow.

7.7.3 Estimating Flow at Individually Calibrated Valves

Home	Avg Error (GPM)	Stdev Error (GPM)	Avg Error (%)	Stdev Error (%)
H1 (7 valves)	0.17	0.13	7.3	6.7
H4 (6 valves)	0.19	0.17	5.6	5.3
H5 (8 valves)	0.13	0.11	4.5	5.5
H7 (8 valves)	0.67	1.47	22.2	46.0

Table 7.5: The results of our flow estimation analysis in four homes. In homes H1, H4, and H5, we are able to estimate flow at individual fixtures throughout the home with error rates comparable to that found in empirical studies of traditional utility-supplied water meters. In H7, placing the sensor on a hot water heater appears to result in a confounding of supply water main pressure with gravitational pressure due to the water in the tank.

It is not unreasonable to imagine that the process of installing a system like HydroSense might include a single calibration of each fixture in a home. In such a scenario, each valve in the home would be labeled with a known R_f value which could be combined with the sensed pressure change ΔP to estimate water flow at those valves.

We examined the accuracy of the flow estimation that might be obtained in this scenario using a cross-validation experiment to analyze the five calibrated bucket trials collected for each of the faucet and shower fixtures in H1, H4, H5, and H7 (as previously discussed in our in-home data collection section). Each trial in the cross-validation used a single calibrated bucket trial to infer a resistance variable R_f for the valve. The inferred value of R_f was then used to estimate flow in the other four trials according to the measured change in pressure ΔP. We then noted the difference between these estimated flow rates (based on the inferred R_f) and their corresponding actual flow rates (obtained through the calibrated bucket trials). The results of this experiment are shown in Table 7.5.

Three of four houses tested (H1, H4, H5) have error rates below 8% (or approximately 0.16 GPM[**]), comparable to the 10% error rates found in empirical studies of traditional utility-supplied water meters (Arregui *et al.*, 2003). The fourth house (H7), however, had an error rate above 20%. We believe this is due to the installation location of the sensor. Whereas the first three homes had HydroSense installed on an exterior water bib, H7's installation used the hot water heater drain valve. This results in two confounding pressure sources (the supply water main and the gravitational pressure of the water in the tank). As previously discussed, our simple pressure model currently assumes a straight pipe. It is likely this situation requires a different model of R_f, and it seems that the cold water valves in H7 were particularly affected. Indeed, removing H7's four cold water valves from our analysis results in an dramatically improved average error of 0.15 GPM (SD=0.18), or 4.5% (SD=3.8%). Because our dataset includes only one home with both hot water heater installation and flow rate information, future work is needed to investigate the feasibility of measuring cold water flow using a sensor installed at the hot water heater drain.

7.7.4 Generalizing to Uncalibrated Valves

In a scenario where only some of the valves in a home have been calibrated, it is reasonable to attempt to build a model of fluid resistance for the entire home from that subset of valves. The key idea here is that, although the pathway to each valve in the home is unique, those paths also share a fair amount of spatial overlap in the length and overall layout of the piping. For example, the toilet and sink in a particular bathroom share the same branch.

To examine this approach, we separated our calibrated bucket trials data into two datasets: a model and a test. The model was initially populated by a single randomly selected trial which was then used to infer a baseline R_f value. We applied this R_f value to calculate a flow estimate for each trial in the test dataset, comparing each to the corresponding actual flow. We next added a second random trial to the model (and removed it from the test dataset), then used the model to create a linear regression ($Q = R_f * \Delta P + b$). This regression was used to calculate flow estimates for the remaining trials in the test set. This process was repeated until all trials had been sampled. To avoid a particularly fortunate or unfortunate random sampling, we repeated this process five times for each home and averaged the results. Figure 7.11 presents the results (note we exclude the cold water valves from H7, consistent with our prior analysis).

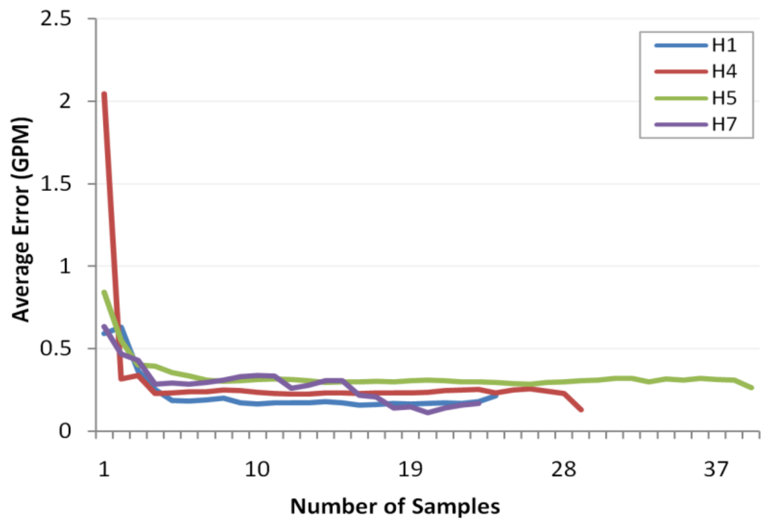


Figure 7.11: Because valves share a fair amount of spatial overlap in the length and overall layout of their piping, it is possible to generalize calibrations across valves.

After sampling five trials, the average error dropped 74% to 0.27 GPM across the four homes and within 0.11 GPM of the more comprehensive R_f data from the previous analysis. This initial result indicates considerable potential for learning to generalize calibrations across valves in a home.

7.8 DISCUSSION

The initial results presented here show significant promise for single-point sensing of whole-home water activity via continuous monitoring of water pressure. We have presented a reliable method for segmenting valve pressure events from their surrounding sensor stream and for determining whether a segmented event corresponds to a valve being opened or closed. Using data collected in ten homes, we have shown >90% aggregate accuracy for identifying the specific fixture and valve associated with a transient using a template-based classification approach. Analyzing flow data collected in four of those homes, we have shown that an appropriately located and calibrated system can estimate water usage with error rates comparable to empirical studies of traditional utility-supplied water meters. Our ability to identify activity at individual fixtures using a single sensor is itself an important advance, and we are not aware of prior work even attempting single-sensor estimation of the amount of water being used at individual valves throughout a home. A particular contribution of HydroSense over other methods (like flow trace analysis, see Chapter 2) is the ability to disaggregate hot and cold water events in a home. Previously, this type of disaggregation required the use of two water meters, one connected to the water supply line into the home and another connected from the supply line of the water heater.

Although our analysis focused on identifying valve events occurring in isolation, it is clearly important to consider the case where multiple events overlap, especially for multi-family homes and apartment units with shared plumbing systems. In Fogarty *et al.*'s prior work with microphone-based sensing, they note an inability to even detect this situation (Fogarty *et al.*, 2006). As an initial investigation, we collected six compound events in H1 (two each of shower/sink, toilet/sink, and shower/toilet/sink overlaps). Our event segmentation algorithm correctly segments these overlapping events (ending the ongoing event when it detects a rapid increase in the magnitude of fluctuation corresponding to the beginning of another event). Preliminary experiments suggest that the magnitude and shape of the events is indeed altered by the overlap. Some aspects of the frequency domain signature remain constant (*i.e.,* high energy harmonics) but we do not have enough compound event data to convincingly evaluate the effectiveness of a classification procedure. Furthermore, events that occur at the *exact* same instant cannot be distinguished as separate events with our current segmentation algorithm. In any case, classification of compound events is a highly important direction for building upon our current results.

An additional limitation relates to how closely our controlled experiments represent naturalistic usage of fixtures (*e.g.,* how often do people partially open valves vs. open them full stop, how is the signal affected by the speed of valve opening or closure). These concerns primarily involve fixtures with manually controlled valves (*e.g.,* bathtubs/showers/faucets) rather than mechanically controlled valves (*e.g.,* dishwashers/toilets/laundry machines). For mechanically controlled valves, the transient is determined based on fixture type (*e.g.,* dishwasher vs. laundry machine) and on its location in the home. For manually controlled valves, the way in which the valve is opened or closed is also a factor (*e.g.,* the speed with which the valve is opened, how much the valve is opened). Our test dataset contains both mechanically and manually operated valves, but our data collection did not explicitly control for different usages of the manually operated valves. Thus, our classification analysis is a first step towards determining the viability of using water pressure waves to classify valves and fixtures in the home.

To address the above limitations, we have conducted longitudinal deployments in multiple households collecting labeled, real-world water usage data. We report on our findings in the next chapter (Chapter 8). Furthermore, we note that the contextual behaviors of water usage are important but not explored in this chapter. Factors such as the time of day (*e.g.,* showers are more likely in the mornings: Mayer *et al.*, 1999), the duration of usage (*e.g.,* toilet refills last between 30-60 seconds depending on the home's water pressure), and temporally cyclic behaviors (*e.g.,* dishwashers and laundry machines use repeated cycles that make identification easier) provide a rich knowledge about water usage and the context of human activity surrounding water usage. Again, these areas are further explored in the next chapter.

In this chapter, we have found that reliable estimation of flow is sensitive to calibration, and we have noted that our segmentation and identification algorithms include threshold parameters that worked well in the homes we studied but are not necessarily ideal. We are interested in developing techniques for automatically calibrating our methods over the course of extended usage. For example, flow estimation could potentially be automatically calibrated through occasional knowledge of whole-home aggregate water usage. Continuing deployments of wireless utility meters make this an increasingly viable approach. We also have initial evidence that system behavior is stable over time, based on a second dataset collected in H1 five weeks after our original collection. We applied our fixture classification methods to this dataset using templates from the opposite dataset (classifying unknown events using templates collected 5 weeks apart), finding no degradation in fixture identification performance. Another argument for stability comes from preliminary analysis of our longitudinal dataset (currently being collected). It shows that static water pressure and outside temperature largely do not affect generated water transients. This preliminary analysis suggests system behavior might be stable enough to apply a variety of machine learning methods for auto-calibration.

Our in-home data collection included installations at several different types of fixtures (hose bibs, utility sink faucets, and water heater drain valves) with generally good results except in houses H9B and H10. There are many examples in Table 7.2 where our current approach differed in its ability to identify the fixture associated with valve open and close events. To help increase the accuracies in H9B and H10, a possible approach is to look at *both* open and close events together before classification. Because events obviously come in a series of opening and closing, it seems natural to pursue an approach that classifies *pairs* of open/close transients rather than individual transients. To investigate the implications of this pairing in H9B and H10, we looked at the number of times a valve open *and* valve close event is classified incorrectly in the same stream (an upper bound on how pairing might perform). Pairing before classification of valve-level events could increase accuracies in H9B to 83% and could increase accuracies in H10 to 81%. We explore pairing in more detail in Chapter 8. Many other factors could be used to increase identification and flow rate accuracies. For example, we currently estimate flow independent of fixture identification, but the two are clearly related and an improved method could consider them simultaneously.

7.9 CHAPTER SUMMARY

We have presented a new approach to single-point infrastructure-mediated sensing of whole-home water activity. Our initial results for the template-based classifier both validate the effectiveness of our approach and provide a basis for future analyses and improvements. The pressure-based sensing strategy shows significant promise as a practical, low-cost, and unobtrusive approach to the broad deployment of sensing-based ubiquitous computing applications in activity inference and real-time eco-feedback. In particular, our approach validates how a single sensor can be used for disaggregated hot and cold water usage, enabling broader and more in-depth studies of the end use of water. In the next chapter, we address many of the limitations enumerated above in a real-world longitudinal deployment of HydroSense.

Chapter 8
A Longitudinal Evaluation of HydroSense with Real-World Water Usage Events

In the previous chapter, we introduced HydroSense, a pressure-based sensing solution that disaggregates water usage at the fixture level from a single installation point. HydroSense identifies the unique pressure waves generated when fixtures are opened or closed. These waves propagate *throughout* a home's plumbing infrastructure, thus enabling the single-point sensing approach. In this chapter, we move from evaluating HydroSense under controlled conditions in staged experiments to evaluating HydroSense via real-world deployments in three homes and two apartments over a five-week period.

At each deployment site, we installed both pressure sensors and a distributed ground truth sensing network directly wired on individual fixtures throughout the home (*e.g.,* kitchen sink, toilet, dishwasher) to provide ground truth labels on the pressure stream. The *ground truth sensors* were designed to track both hot *and* cold water usage at their respective fixtures. This allowed us to investigate not only whether the pressure signal could be used to infer fixture-level water activity but also whether it could be used to determine hot and/or cold water usage at each fixture. This is an important capability, as noted in Chapter 2, as water heating alone is responsible for 12.5% of residential energy consumption (U.S. Department of Energy, 2001). To our knowledge, our ground deployment represents one of the most comprehensive real-world studies of hot and cold water usage in residential homes and apartments ever performed.

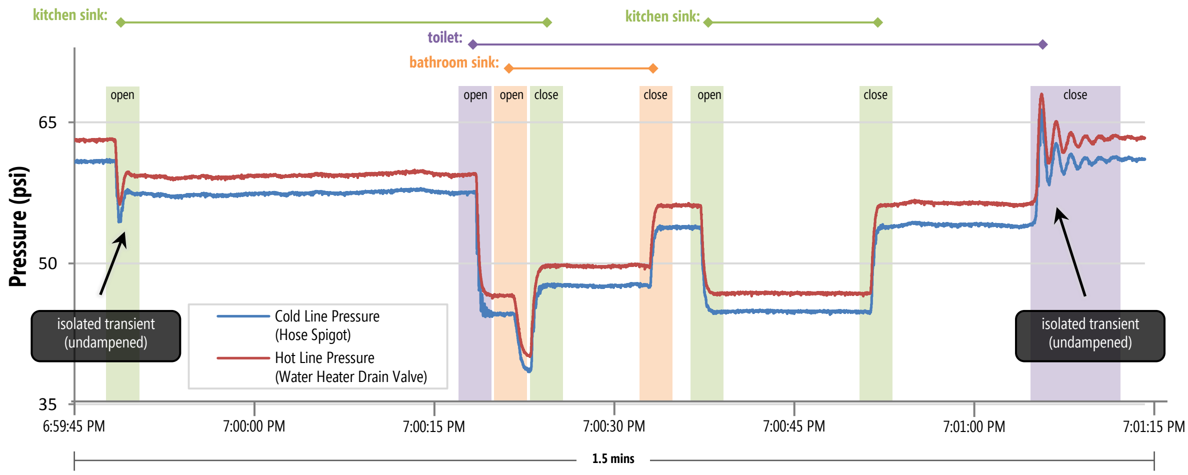


Figure 8.1: A pressure stream with ground truth labels from deployment site H2. The blue line is the cold water pressure (sensed from a hose spigot) and the red line is the hot water pressure (sensed from a water heater drain valve). The pressure transients are also highlighted and colored according to fixture. Note how rapid increases and decreases in pressure correspond to opens and closes and how transient waveforms are dampened when they occur in compound.

Over five weeks, we collected approximately 15,000 ground truth labels for the opening and closing of fixture valves (*e.g.,* Figure 8.1). The scope and size of this dataset allows us to examine the practical challenges in constructing water usage activity inference algorithms and to highlight problems that any *indirect* water sensing method must address. We show, for example, that compound events (when two or more water fixtures are operating at the same time) constitute 37.1% of all bathroom sink activity and nearly 20% of overall water usage activity. Such prevalence suggests that compound events should be specifically addressed and evaluated by any water disaggregation technique; however, this has rarely been the case (*e.g.,* Fogarty *et al.*, 2006; Kim *et al.*, 2008; Wilkes *et al.*, 2005). Thus, our ground truth data serves both as a resource to inform the design of our classification algorithms as well as to evaluate their performance.

We use the ground truth labels along with the pressure stream data to design and evaluate a novel pressure-based water usage inference algorithm. Although the template matching of pressure wave transients used in the previous chapter worked well for controlled experiments, we show that a template-matching approach alone is insufficient for the variety of signal distortions that occur during real-world water use. For example, the speed with which a faucet handle is turned and whether an event occurs in isolation or in compound can change the shape of the pressure transient thereby rendering the naïve template matching approach inadequate. Consequently, we extend and adapt the original HydroSense algorithms to use a probabilistic model based in part on speech recognition algorithms. We show how the addition of a language model and contextual priors (*e.g.,* fixture usage duration, and maximum flow rate) can boost classification accuracies by an average of

6% with real-world water usage data. We also show that the introduction of a language model and priors decreases the amount of training data relative to a template-based approach alone. Our current analysis provides pre-segmented pressure transients to our classification algorithm, leaving segmentation to future work. In this way, our classification results can be seen as an upper bound.

In summary, the contributions of this chapter are: (1) The most comprehensive dataset of labeled real-world hot and cold water usage events ever collected in homes and apartments; (2) An analysis of our new real-world dataset to uncover challenges that any indirect sensing water disaggregation method must overcome; (3) A new probabilistic approach to water usage classification that is highly extensible and incorporates a language model, grammar, and contextual priors; (4) An evaluation showing that this new probabilistic approach performs significantly better than previous template-based methods.

8.1 DATA COLLECTION AND DEPLOYMENT

To evaluate the performance of a pressure-based approach using *real-world* data, we deployed a large ground truth water usage sensing network in three homes and two apartments. At each deployment site, we installed two pressure sensors and directly instrumented *all* water fixtures and appliances with custom wireless sensors that provided ground truth labels of water usage activity for the pressure stream. Here, we describe the ground truth data collection system and the five week study deployment.

8.1.1 Acquiring Ground Truth Labels in a Real-World Deployment

A key challenge in evaluating any new sensing technique is acquiring ground truth data. In the original HydroSense work (Chapter 7), the team *manually* labeled the pressure stream during their staged experiments, which clearly would not work for a real-world evaluation. Thus, an automated method for labeling must be derived. An ideal labeling system would accurately detect when fixtures are turned on/off, be easy to install, work across a large variety of fixtures, and preferably provide flow and temperature information for each fixture valve. An accurate and direct approach would be to install small, wireless flow meters at each hot and cold fixture inlet (*e.g.,* a sink would require two flow meters). Unfortunately, inline flow meters could actually distort the very phenomena we are interested in studying by impacting the pressure-wave signal itself. Instead, we instrumented fixtures externally, such as on faucet and toilet handles, so that we did not disturb the water stream.

We designed an array of ground truth sensors to accommodate the variety of home water fixtures: from hand operated fixtures like sinks to electromechanical appliances such as dishwashers. Even for a single fixture type, design variation affects how flow and temperature are selected and how they can be sensed. For example, some single-handle faucets move left to right for temperature and up or down for flow while dual-handle faucets select both temperature and flow by the open position of each handle.

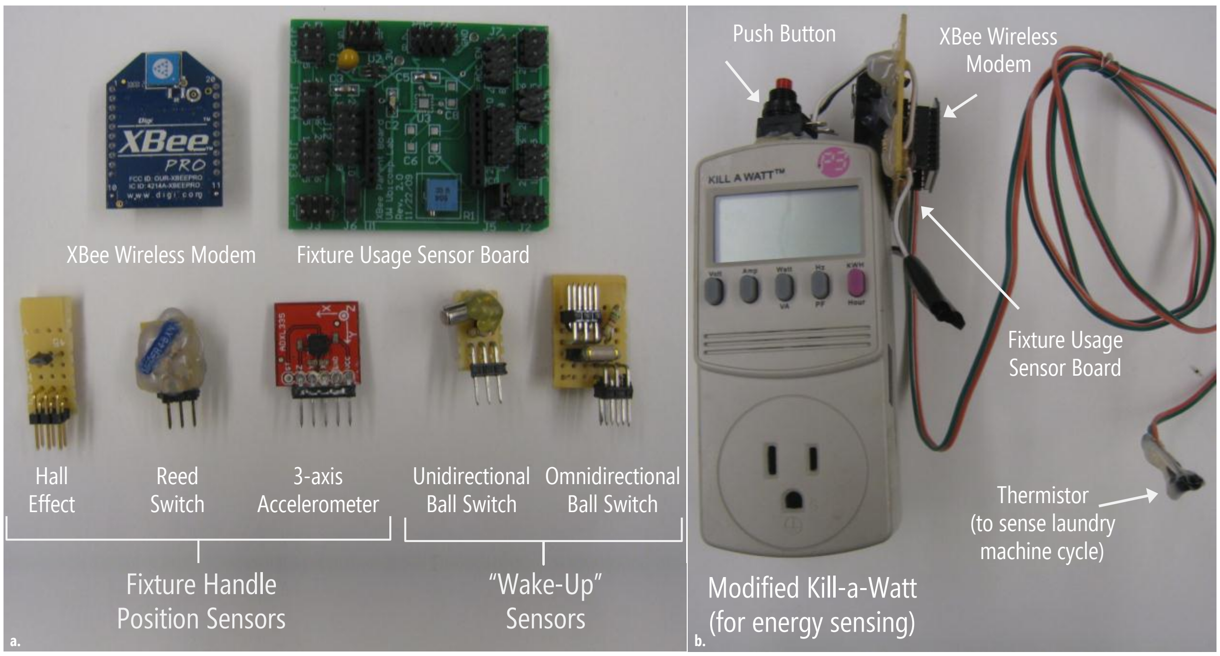


Figure 8.2: The ground truth water usage sensors directly attached to (a) *fixtures* and (b) *appliances* and monitored valve openings and closings. The "wake-up" sensors would activate on handle movement causing the fixture usage sensor board to read from one or more of the fixture handle position sensors. This data was then transmitted wirelessly in real time via an XBee wireless modem to an onsite data logger.

8.2 WATER USAGE ACTIVITY GROUND TRUTH SENSORS

We developed seven ground truth sensors to accommodate all fixtures across our deployment sites. Each interfaced with a *parent sensor board* (wireless platform Figure 8.2a, top right) to communicate water usage data in real time. At a minimum, we tracked when each valve was opened or closed and categorized temperature into *hot only*, *cold only*, and *mixed*. The parent sensor board was placed in a location protected from water and preferably next to a power outlet (5 of 33 ground truth sensor boards relied on battery power). All sensors and parent boards were weatherproofed to protect against water damage. XBee Pro wireless modems (Figure 8.2a, top left) transmitted sensor state to a logger on a laptop installed at each deployment site. The sensor boards were configured to transmit a watchdog signal once every four minutes so failures could be quickly identified and corrected. The ground truth architecture and sensors went through several design cycles and took approximately three months to build and evaluate before being deployed in this study.

Figure 8.3: (a) Accelerometers were used on single handle faucets to track flow and temperature position; (b) A modified Kill-a-Watt tracks the laundry machine's energy use to indirectly monitor water consumption—a thermistor was placed in the drain pipe to discriminate temperature settings. (c) In H1, we used a reed switch configuration to track refrigerator dispenser water usage.

For sinks, showers, and toilets, sensors to detect handle position were affixed directly to the fixtures themselves and linked to the wireless parent board via low-voltage wires (Figure 8.3 and Figure 8.4). We used three types of handle sensors: *reed switches* (*N*=34 sensors deployed), *accelerometers* (*N*=14), and hall effect *sensors* (*N*=3). Reed switches are electrical switches that react to the presence of a magnetic field and produce binary output: on or off. They are inexpensive, robust to water exposure, and provide easily analyzable data. For toilets, we instrumented the flush handle, which only provided data on the beginning of the fill and not on the end. We discuss how this end fill information was recovered in the next section.

For faucets where a single handle controls flow rate and temperature, the reed switches were insufficient. Instead, we used three-axis accelerometers (*e.g.,* Figure 8.3a, Figure 8.4a, b, and f) to measure acceleration and interpret the handle's flow position (typically up and down movement) and temperature (typically left and right movement). Finally, we used hall effect sensors for sensing faucets which control temperature using planar rotation but control flow through an up/down motion (*i.e.,* where an accelerometer alone could not sense the planar motion). A hall effect sensor provides a voltage difference representing the distance between two magnets, so we placed magnets on both sides of faucet handles and attached the hall effect sensor to the handle itself.

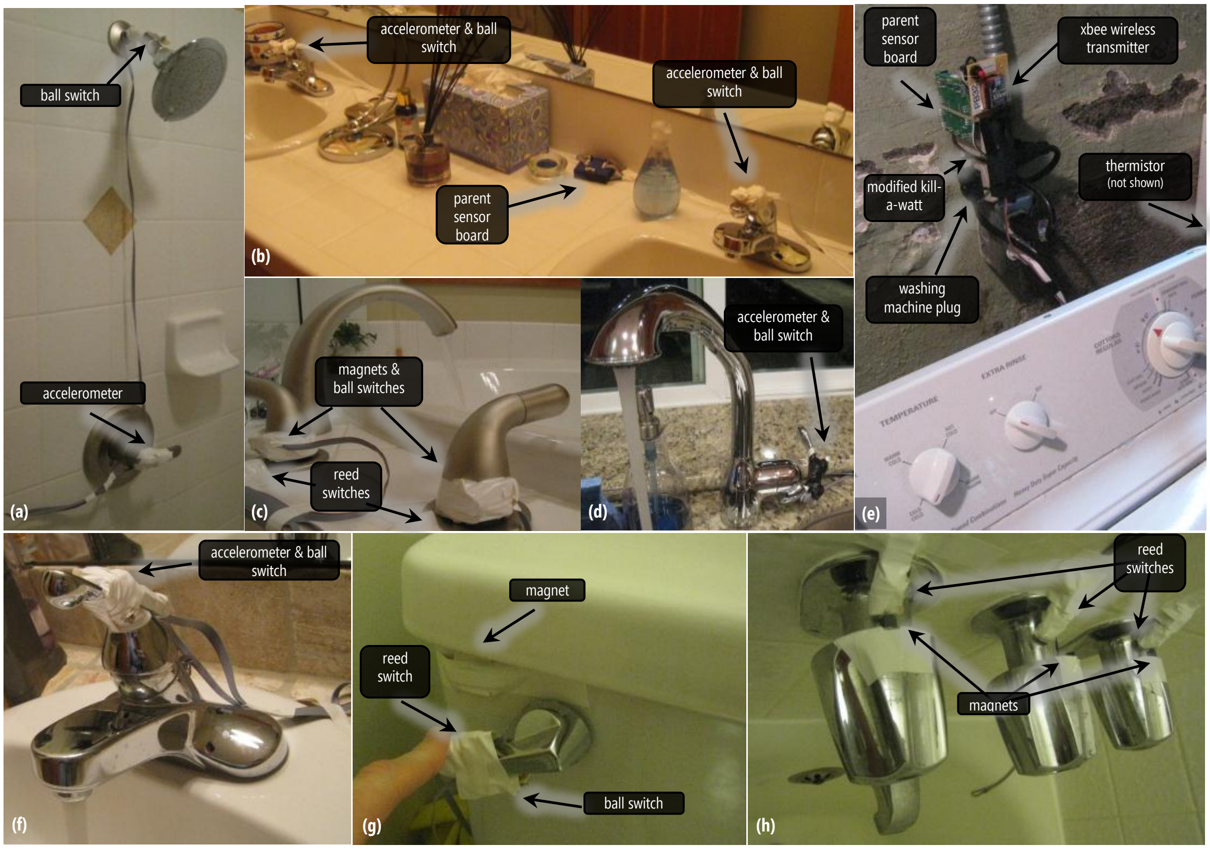


Figure 8.4: A sample of instrumented fixtures from our ground truth deployments. Note how different sensors (*e.g.*, accelerometers and reed switches) are used to accommodate the variety of fixture types.

Additionally, each hand-operated fixture had at least one omni-directional *ball switch* (*N*=39) that acted as a vibration sensor and woke the parent board to read and transmit handle position sensor data. This allowed us to limit power consumption and unnecessary XBee wireless traffic.

For washing machines and dishwashers, we used three types of sensors: *power usage sensors* (*N*=7)**,** *push buttons* (*N*=2), and *thermistors* (*N*=3). Power consumption patterns were used to reconstruct when appliances used water. We could not gain access to the power outlets in two cases (deployment site A1's washing machine and H1's dishwasher), so we used push buttons and a note reminding the resident to "*please push button when turning on <appliance>*." For sites with washing machines, we also attached thermistors to the water drain pipe to measure the temperature of the previous fill cycle and infer machine settings (*e.g.,* Hot/Cold or Warm/Cold).

8.2.1 Pressure Sensors and Software Tools

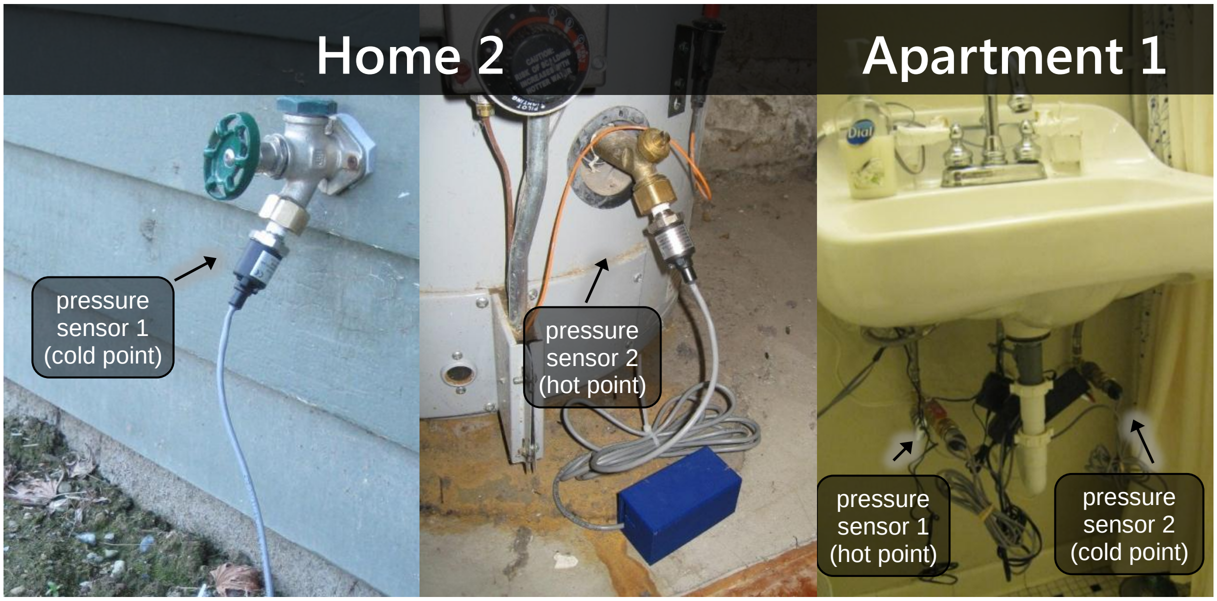


Figure 8.5: Two pressure sensors were installed at each deployment site (one on a hot water access point, one on a cold) to study the effect of installation points on classification accuracies.

The above sensor network was deployed at each deployment site to provide *ground truth labels* for our pressure sensors. For our pressure sensors, we used Pace Scientific P1600s with a resolution of 0.03 psi (the same hardware from Chapter 7). Each was connected to a 16-bit Texas Instruments ADS8344 ADC and AVR microcontroller, which interfaced with a Class 1 Bluetooth radio implementing the serial port profile with an approximate wireless range of 10m. This is the same setup as the original HydroSense study with three exceptions. First, instead of one pressure sensor, we connected *two* sensors to collect data from hot *and* cold water access points simultaneously (Figure 8.5). This allowed us to investigate the effect of installation point as well as the effect of two pressure streams compared to one on classification performance. Second, the original HydroSense work tested only $^{3}/_{4}$" water access points (*e.g.,* hose spigot). We built adapters to connect to $^{3}/_{8}$" access points, which allowed us to install pressure sensors below kitchen and bathroom sinks (Figure 8.5, right). This was particularly important for the apartment installations, which did not have accessible $^{3}/_{4}$" access points. Finally, we used a sampling rate of 500Hz rather than 1,000Hz, as we found 500 Hz was more than sufficient to capture these pressure waves.

To communicate with the ground truth sensor network and the pressure sensors, a 2GHz Dell Inspiron 1545s laptop running Windows XP was deployed at each site. The laptops were configured with a USB XBee wireless modem and Bluetooth dongle. The laptops continuously ran a custom data logger written in C#, which received, compressed and archived data locally for backup. This was uploaded to a backend webserver at 30-minute intervals. The server backend was implemented using Python and web2py. In addition to serving as a data repository, the backend automatically sent e-mail notifications when a ground truth sensor or pressure sensor was not heard from for 10 minutes or more. For analysis, we constructed a suite of tools in Matlab and C#. Because not all of the ground truth sensors provided direct labels about water usage (*e.g.,* the power usage sensors and toilet handle sensors), we also built a custom annotation tool in C# that allowed us to quickly review the ground truth sensor streams and semi-automatically annotate the pressure stream (see Figure 8.6, Figure 8.7, and Figure 8.8).

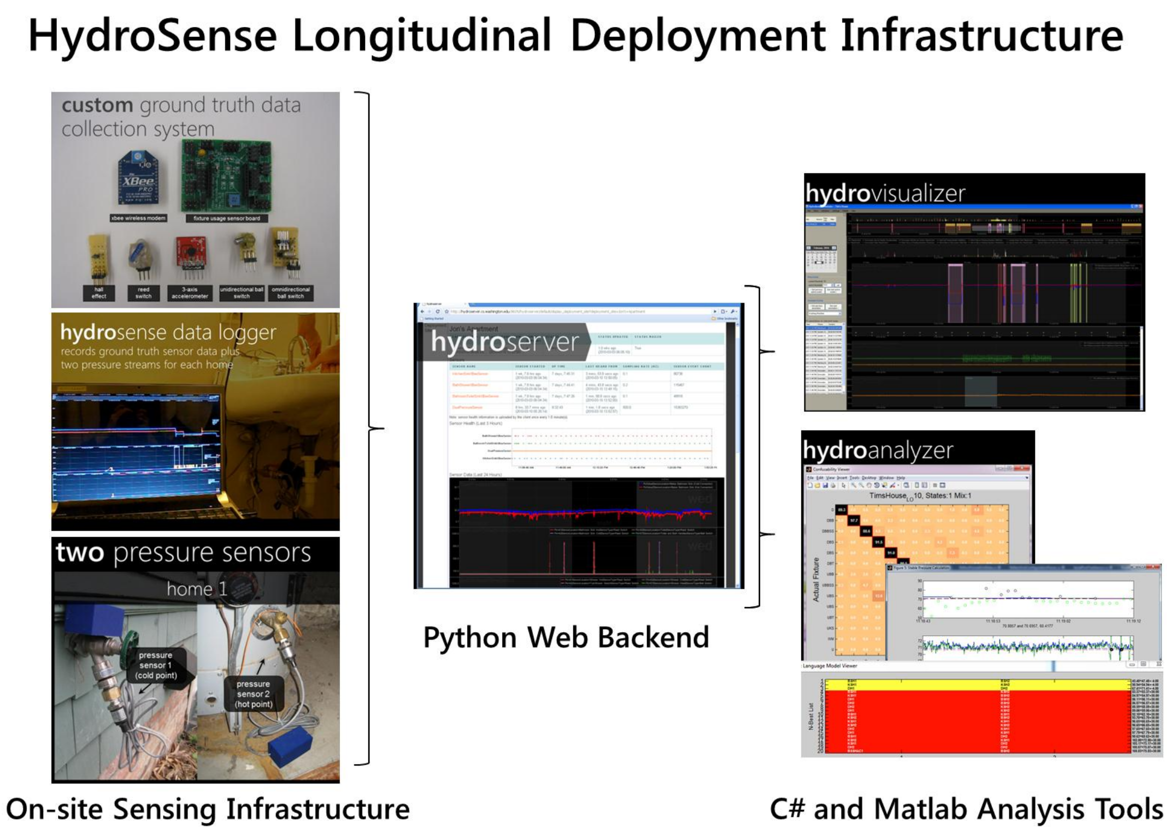


Figure 8.6: The HydroSense longitudinal deployment infrastructure included: (i) a custom ground truth sensor on each water valve in the home; (ii) two pressure sensors: one installed on hot line, one on cold line; (iii) an updated version of the HydroSense Logger from Chapter 7 that communicated with the ground truth sensor network (XBee) and the pressure sensors (Bluetooth), visualized this data in real-time, and uploaded it to a web server; (iv) a Python web backend that received data from each deployment site in 30-minute chunks and also served as a watchdog service to alert research team of possible sensor failure; (v) a HydroSense Visualization and Annotation tool that allowed us to explore the gigabytes of collected pressure stream and ground truth data in a zoomable interface; (vi) a suite of Matlab analysis and visualization tools.

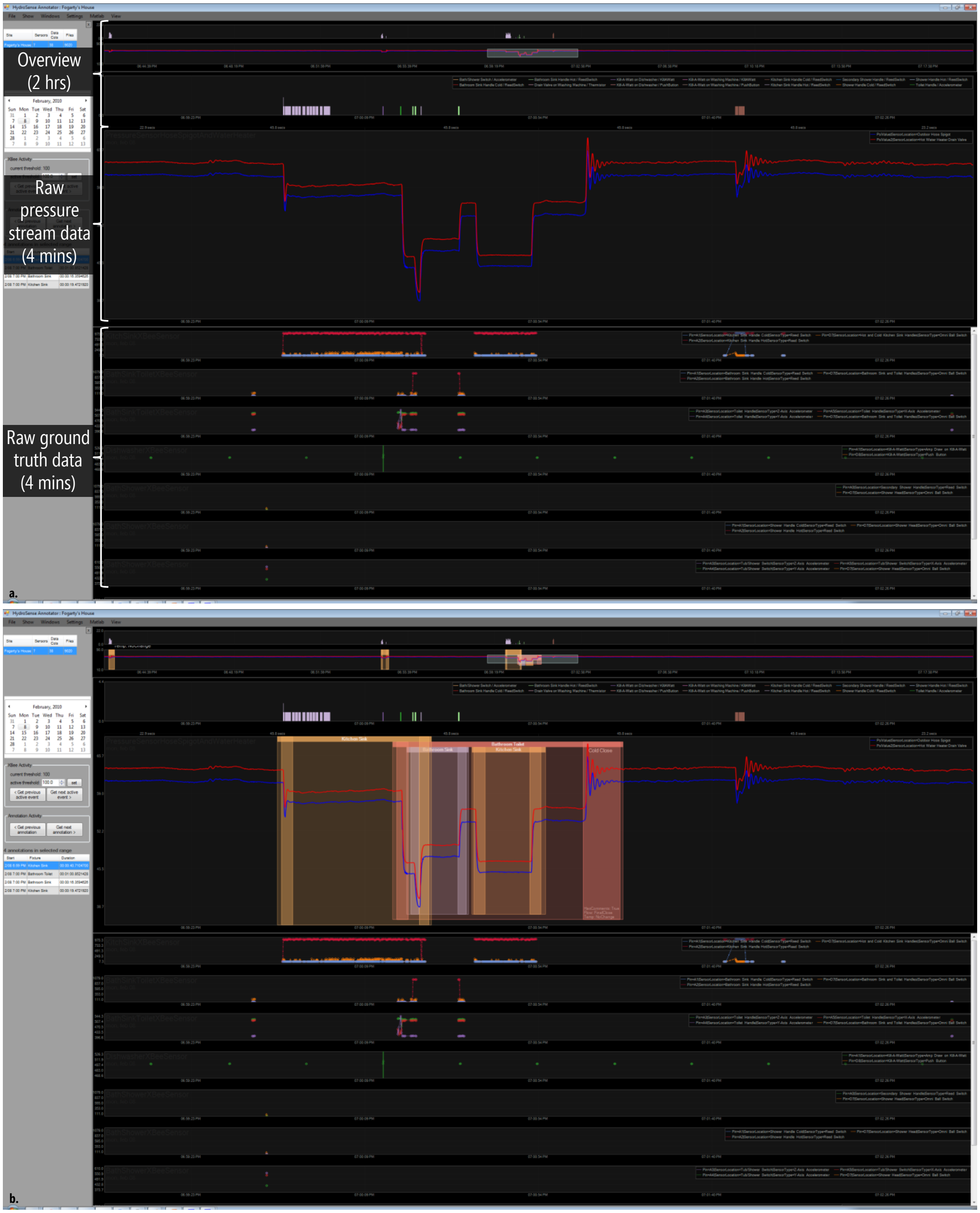


Figure 8.7: The HydroSense Visualization and Annotation tool was used to visualize the gigabytes of pressure stream data and ground truth data from each deployment site. The tool allowed us to semi-automatically convert the ground truth data to semantic labels. (a) Shows approximately four minutes of hot/cold pressure stream data and ground truth data from H2. (b) The same view with the ground truth data converted to labels.

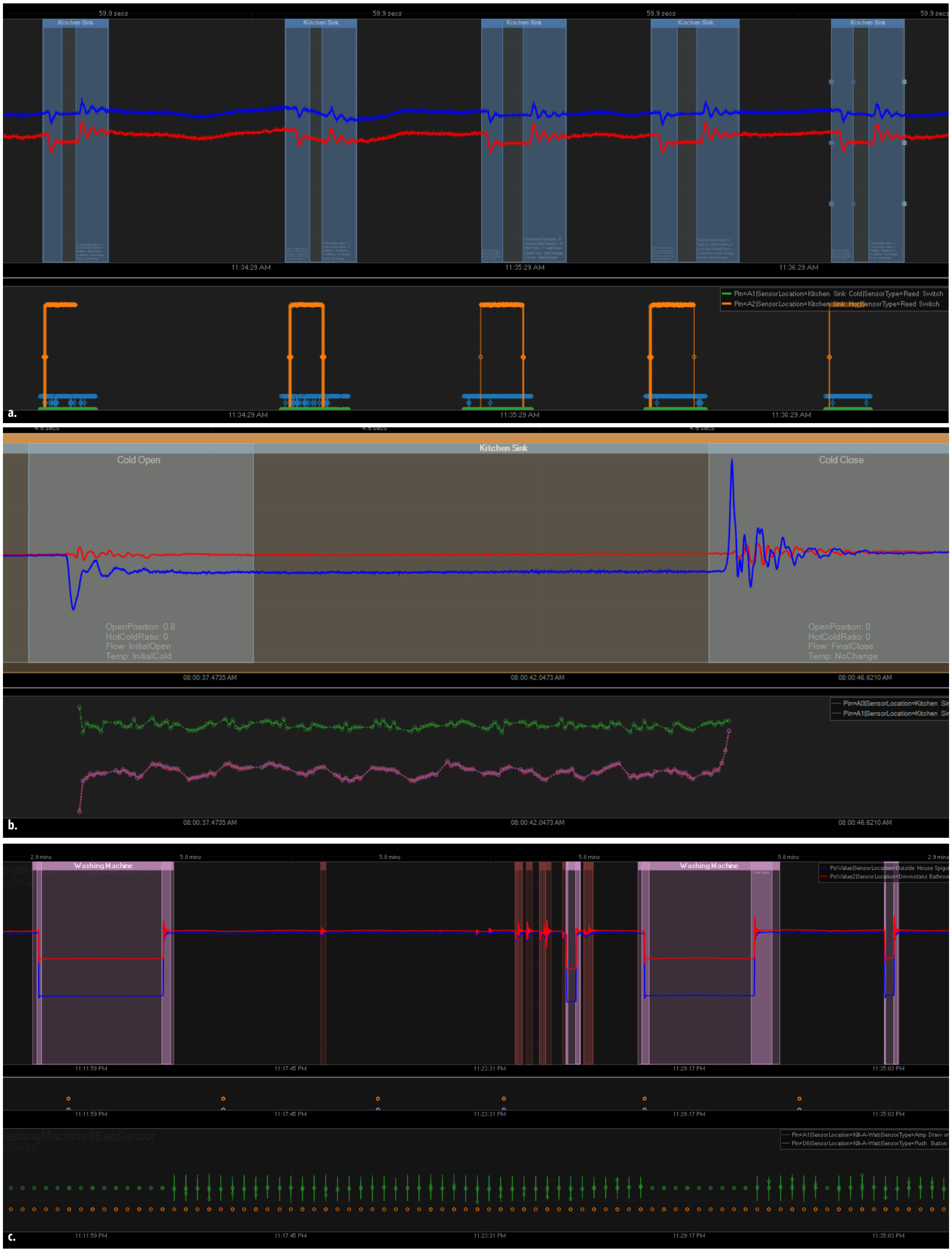


Figure 8.8: Three different examples of pressure streams and accompanying ground truth data. (a) Kitchen sink usage in A1 with reed switch ground truth data visualized below. (b) Kitchen sink usage in A1 with hall effect ground truth data visualized below. (c) Washing machine usage in H3 (violet annotations) with Kill-A-Watt power consumption data visualized below.

8.2.2 Deployments

We deployed the ground truth sensor network and two pressure sensors at five sites: three houses and two apartments. Each site was a home or apartment of one of the research team members. This was done because of the invasiveness of the direct sensing approach used for the ground truth data collection. There was, however, a large variation in the type, size and plumbing systems across the deployments sites (Table 8.1). The deployments began February 2010 and lasted for five weeks.

It took approximately two full work days per deployment site for two people to install and test the ground truth sensors. After the five-week ground truth deployments ended, we used our custom annotation tool to convert the ground truth sensor stream to labels. This was accomplished in a semi-automatic fashion—the annotation tool visualized the ground truth sensor values and the pressure streams together in a common time-series view. The ground truth sensor values could then be automatically or manually converted to labels. It took approximately 8-12 hours per week of data collected for one research assistant to convert the sensor stream to labels. These labels were then reviewed by a second research assistant for consistency, which took roughly half the time (4-6 hours per week of data).

8.3 ANALYSIS OF THE COLLECTED DATASET

	H1	H2	H3	A1	A2
# Residents	2	2	4	2	2
Gender/Age/ Profession	M/27/professor; F/29/professor	M/31/professor; F/32/office worker	4 Males/19-21/ undergrad students	M/31/grad student; F/30/post-doc	M/26/grad student; F/26/pharmacist
Fixtures/Valves	17/28	8/13	13/21	6/10 *(8/13)**	8/13
Style/Built	House/2003	House/1918	House / 1923	Apt/1920s	Apt/2000
Size/Floors	3000 sqft/ 2 floor + basement	750 sqft/ 1 floor + basement	1200 sqft / 1 floor + basement	700 sqft/ 3rd floor of 3	750 sqft/ 6th floor of 7
Expansion Tank/ Regulator	Yes/Yes	No/No	No/No	Unknown/ Unknown	Unknown/ Unknown
Water Heater Tank Size/ Plumbing	50 gal/ Copper	50 gal/ PEX	50 gal/ Copper	Two 100 gal tanks/ galvanized	Unknown/ PEX
Pressure Sensor Install Point Hot/Cold	Main floor bathroom sink/ outdoor hose spigot	Water heater drain valve/outdoor hose spigot	Downstairs bathroom sink/ outdoor hose spigot	Bathroom sink hot/cold inlet	Kitchen sink hot/cold inlet

Table 8.1: Occupant demographics and deployment site characteristics. In A1, The toilet and shower head were replaced with low-flow equivalents ~3.5 weeks into the deployment. We discuss the effect of this change on classification performance in the results section.

We collected a total of 16,056 labeled events across the five deployment sites. Table 8.2 provides an overview. Due to ground truth sensor failures, 2.9% of this data is marked as *uncertain* and is not used in our classification experiments. Nearly 80% of the uncertainties were due to malfunctioning kitchen sink handle position sensors in H1 and H2, which were replaced within a few days of discovery. The dataset also includes *unknown* events (3.9% of our dataset), which are pressure stream transients whose origin cannot be determined because they occurred without accompanying data from the ground truth sensors. A1 has the highest proportion of unknown events (9.1%) because of water usage activity coming from other apartments. Although we do not attempt to classify uncertain or unknown events, they were not removed from the dataset and can impact classification performance when they overlap with other events. After accounting for uncertain/unknown events, we are left with 14,960 labels.

	H1	H2	H3	A1	A2	Totals
Days of Data	33	33	30	27	33	156
Total Events	2374	3075	4754	2499	2578	14960
Avg Events/Day	71.9	93.2	158.5	92.6	78.1	95.9
Cold Only Events	855 (36.0%)	1418 (46.1%)	1637 (34.3%)	633 (25.3%)	1657 (64.3%)	6087 (40.7%)
Hot Only Events	607 (25.6%)	1329 (43.2%)	1766 (37.5%)	1818 (72.8%)	498 (19.3%)	5870 (39.2%)
Mixed Temp Events	912 (38.4%)	328 (10.7%)	1351 (28.2%)	48 (1.9%)	423 (16.4%)	3003 (20.1%)
Isolated Events	1981 (83.5%)	2477 (80.6%)	4131 (86.9%)	1914 (76.6%)	2149 (83.4%)	12393 (82.8%)
Compound Events	393 (16.6%)	598 (19.5%)	623 (13.1%)	585 (23.4%)	429 (16.6%)	2567 (17.2%)
Transient Collisions	142 (6%)	72 (2.3%)	166 (3.5%)	219 (8.8%)	120 (4.7%)	701 (4.7%)
Uncertain Events	22 (0.9%)	175 (5.3%)	189 (3.7%)	52 (1.9%)	37 (1.4%)	467 (2.9%)
Unknown Events	52 (2.1%)	79 (2.4%)	184 (3.6%)	254 (9.1%)	85 (3.1%)	629 (3.9%)

Table 8.2: High level ground truth data collection statistics. An event is one occurrence of either a valve open or a valve close. Uncertain and unknowns are not included in the totals events row.

Table 8.3 shows valve activity at individual fixtures by temperature state (hot, cold, and mixed). We use *M.* for Master and *S.* for secondary to distinguish primary and secondary bathrooms. The *M. Bath Diverter* and *S. Bath Diverter* are for the tub/shower switch that diverts water flow from the bath to the shower and vice versa; we distinguish between a shower that is turned on straightaway and a shower that is diverted from a bath. The *Other* category includes data from only one deployment site, H1, and encompasses the *Laundry Basin* and the *Refrigerator Water Dispenser*. On average across all deployment sites, there is a nearly even proportion of cold and hot events (40.7% for cold only, 39.2% for hot, and 20% for mixed). This implies that any indirect water disaggregation sensing method, such as flow-trace analysis and HydroSense, must be equally capable of sensing usage regardless of temperature. The overall frequency of fixture usage follows a power-law distribution where the first four fixtures (*kitchen sink, master bathroom sink* and *toilet,* and *secondary bathroom sink*) account for 84.7% of the events in our dataset. For purposes of human activity inference, these fixtures are thus critically important.

Fixtures	Count	Total	Hot	Cold	Mixed	Compound	Collision	AvgDuration
KitchenSink	5	5494 (36.7%)	2438 (44.4%)	1415 (25.8%)	1641 (29.9%)	342 (6.2%)	206 (3.7%)	22.4 secs
M.Bathroom Sink	7	3934 (26.3%)	2114 (53.7%)	1294 (32.9%)	526 (13.4%)	1459 (37.1%)	185 (4.7%)	27.2 secs
M.Bathroom Toilet	5	1886 (12.6%)	0 (0.0%)	1886 (100%)	0 (0.0%)	87 (4.6%)	117 (6.2%)	43.6 secs
S.Bathroom Sink	4	1369 (9.2%)	618 (45.1%)	637 (46.5%)	114 (8.3%)	430 (31.4%)	57 (4.2%)	30.9 secs
Washing Machine	4	430 (2.9%)	93 (21.6%)	325 (75.6%)	12 (2.8%)	12 (2.8%)	66 (15.3%)	1.6 mins
M.Bathroom Bath	5	423 (2.8%)	224 (53%)	35 (8.3%)	164 (38.8%)	87 (20.6%)	20 (4.7%)	43.4 secs
S.Bathroom Toilet	3	341 (2.3%)	0 (0.0%)	341 (100%)	0 (0.0%)	11 (3.2%)	21 (6.2%)	27.2 secs
M.Bathroom Shower	5	261 (1.7%)	55 (21.1%)	4 (1.5%)	202 (77.4%)	30 (11.5%)	10 (3.8%)	8.7 mins
Dishwasher	3	261 (1.7%)	261 (100%)	0 (0.0%)	0 (0.0%)	9 (3.4%)	6 (2.3%)	1.2 mins
M.Bath Diverter	5	228 (1.5%)	17 (7.5%)	1 (0.4%)	210 (92.1%)	92 (40.4%)	5 (2.2%)	N/A
Other	1	181 (1.2%)	28 (15.5%)	149 (82.3%)	4 (2.2%)	0 (0.0%)	4 (2.2%)	8.2 secs
S.Bathroom Bath	2	59 (0.39%)	5 (8.5%)	0 (0.0%)	54 (91.5%)	2 (3.4%)	2 (3.4%)	20.7 secs
S.Bathroom Shower	2	47 (0.31%)	11 (23.4%)	0 (0.0%)	36 (76.%)	0 (0.0%)	1 (2.1%)	9.4 mins
S.Bath Diverter	2	46 (0.31%)	6 (13%)	0 (0.0%)	40 (87%)	6 (13%)	1 (2.2%)	N/A
Totals	53	14960	5870 (39.2%)	6087 (40.7%)	3003 (20.1%)	2567 (17.2%)	701 (4.7%)	49.1 secs

Table 8.3: A breakdown of valve activity by fixture, by temperature state (hot, cold, mixed) and by compound/collisions. The Count column tabulates the number of fixtures across sites.

Although we ultimately used this data to evaluate our classification algorithms, an equally important goal was to identify potential challenges in classifying real-world water usage compared to simulated, isolated water events. A *compound valve event* is a valve event that occurs while another fixture is using water (*e.g.,* the bathroom sink events in Figure 8.9a). A *collision valve event* is a valve event that occurs within *two seconds* of one or more other valve events (Figure 8.9b and c). Previous water disaggregation sensing approaches have performed poorly in the face of compounds and collisions (*e.g.,* Fogarty *et al.*, 2006; Wilkes *et al.*, 2005). This is because compounds and collisions often mask or distort features used for classification. Although a collision is technically also a compound, for the purposes of our analysis we separate them to investigate the individual effect of each on classification performance. In our dataset, 17.2% of all valve events are compound while 4.7% of valve events are collisions (Table 8.2 and Table 8.3). The most common compound/collision events are master bathroom sink opens and closes, comprising 41.8% of all bathroom sink activity and 11% of all valve activity overall (Table 8.3).

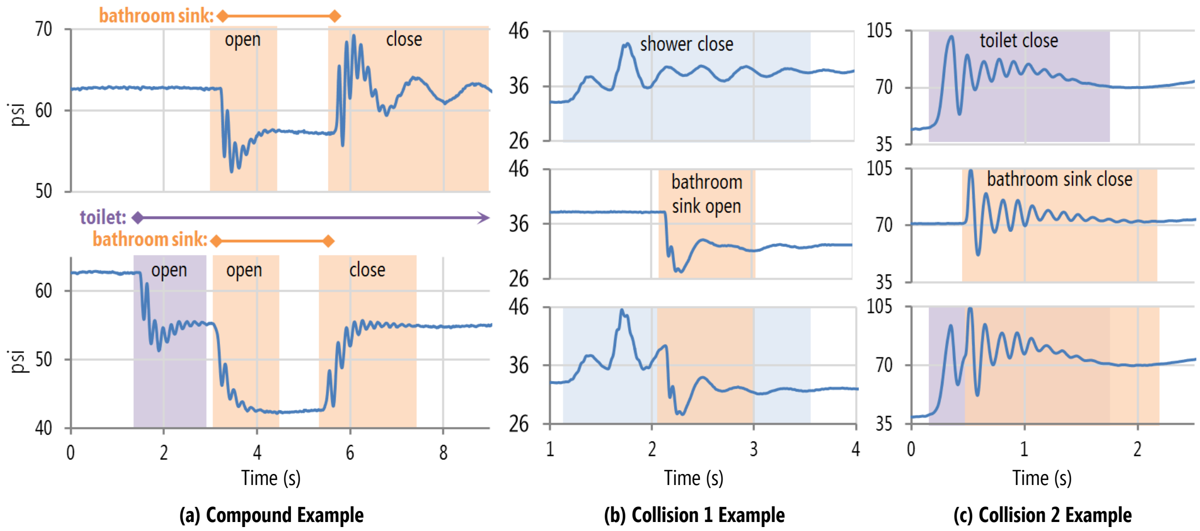


Figure 8.9: (a) Bathroom sink open and close transients occurring in isolation and in compound from H2. (b) A shower close and bathroom sink open transient in isolation and colliding from A2. (c) A toilet close and a bathroom sink close transient in isolation and colliding from H3.

With the pressure-based approach, compound valve events result in a dampening and often a severe attenuation of the high frequency component of the pressure transient. As a result, the transient signal is homogenized, making it difficult to classify. With collisions, the two colliding transient waveforms become highly distorted; although it is rarely the case that two transients occur simultaneously (more often they are offset by 200-500ms), the distortions may still render the transient unrecognizable. In Figure 8.9b, the shower close and bathroom sink open occur 1.1 seconds apart. In Figure 8.9c, the toilet close and bathroom sink close occur 200 milliseconds apart, making it unlikely that both will be classified. For these events to be classified correctly, less emphasis may need to be placed on template matching transient signatures relative to the original HydroSense work (Chapter 7). Our new algorithm specifically attempts to address this issue.

8.4 VALVE EVENT CLASSIFICATION ALGORITHM

To classify pressure transients as valve events, we apply a probabilistic approach using Bayesian estimation. Our particular approach is inspired by the dynamic Bayesian models used in speech recognition. Instead of recognizing *words,* we recognize *valve events*. Like many of the Bayesian approaches used in speech recognition, we incorporate a language model and grammar, which estimates the most likely *sequence of valve events* and defines permissible *valve event pairings*. This provides robustness against transient deformations that can occur during natural valve usage (*e.g.,* brief water usage events, low-flow, and compounds).

At a high level, the classification algorithm works as follows: First, an incoming water pressure data stream is buffered and the pressure transients are segmented. This segmentation process currently uses the time series boundaries defined by the ground truth annotations but would be automated in an end-to-end system. We note, however, that the event identification and segmentation algorithm in Chapter 6 performed with perfect accuracy. More work will be needed for these algorithms to adapt to pressure streams that include compounds and collisions; we return to this limitation at the end of the chapter in the discussion section. Second, the segmented pressure transients are each compared to a library of labeled templates using a set of similarity algorithms. Third, a language model determines the likelihood of a given sequence of valve signatures and links *open* and *close* valve events into *paired tuples.* Fourth, we extract features from these paired tuples and compare them with smoothed probability distributions. For example, by pairing a *bathroom sink hot open* with a *bathroom sink hot close*, we can extract the *duration* of that event and estimate the *total flow volume* used and then obtain probabilities for those features. Finally, the probabilities from the previous three steps are multiplied together for each sequence and the sequence with the highest probability is selected.

We now formally define our Bayesian model for classifying pressure transient sequences. In eq. (8.1) below, let **V** denote the pressure signature template library (a vector of labeled pressure transient signatures and their transforms) and **S** denote a sequence of *unknown* segmented pressure transients. Then, using Bayes' theorem, the most likely valve sequence is defined as:

$$\hat{V} = \arg\max P(\mathbf{V} \mid \mathbf{S}) = \arg\max \frac{P(\mathbf{S} \mid \mathbf{V}) P(\mathbf{V})}{P(\mathbf{S})} \qquad \textbf{(8.1)}$$

The conditional probability term $P(\mathbf{S}|\mathbf{V})$ describes the outcome of the *template-* and *feature-based comparisons.* The prior probability term $P(\mathbf{V})$ describes the likelihood of the valve sequence (using bigrams) and the likelihood of each pairing in the sequence. Note that *arg max* simply returns a specific valve sequence rather than a probability estimate, thus the normalization constant $P(\mathbf{S})$ can be discarded in practice. We can expand the numerator of eq. (8.1) to further highlight the four major components of our approach:

$$\overbrace{\underbrace{\prod_{r=0}^{R-1} f_r(\hat{\mathbf{S}}_r \mid \hat{\mathbf{V}}_r)}_{\text{(i) templates and signal features}}}^{P(\mathbf{S}|\mathbf{V})} \overbrace{\underbrace{\prod_{n=0}^{N-1} P(v_n \mid v_{n-1})}_{\text{(ii) bigram language model}} \underbrace{\prod_{i \notin \beta} f_p(v_i)}_{\text{(iii) grammar}} \underbrace{\prod_{k=0}^{K-1} \prod_{\langle a,b \rangle \in \beta} f_k(\langle v_a, v_b \rangle)}_{\text{(iv) paired valve priors}}}^{P(\mathbf{V})} \qquad \textbf{(8.2)}$$

$P(\mathbf{S}|\mathbf{V})$ is now represented by the first term in eq. (8.2), which describes our set of R signal transformations and comparison algorithms (where f_r is the comparison algorithm for the rth transformation). $P(\mathbf{V})$ is expanded into three terms: our bigram language model, a grammar, and water usage event priors. We describe each term in the following.

8.4.1 Term (i): Template- and Feature-Based Comparison

Term (i) compares the segmented unknown pressure transient s with *open* and *close* valve templates in our library. Each comparison is broken into two parts: a *signal transformation* on s to achieve $\hat{s}$ and a *similarity score* calculation between $\hat{s}$ and a corresponding transformed valve template $\hat{v}$ in our template library. We use multiple signal transformations and comparison algorithms to produce a set of similarity scores for a given valve (each transformation and score is represented by f_r in term (i)). These scores are converted into probabilities and multiplied together to form a single template-match probability between s and every valve v in the template library. This is similar to the original HydroSense algorithm works as described in Chapter 7 which used a hierarchical classifier to prune and classify these individual pressure transients. Unlike this earlier work, however, these similarity scores are incorporated into a probabilistic model.

We use eight signal transformations—four filters and a Cepstral transform of each filter. Each attempts to emphasize a unique property of the pressure transient waveform. The first two filters, a 1 Hz and a 13 Hz low-pass filter, allow us to explore the temporal shape of the transient signal. The next two filters are *derivatives* of the low-pass filtered signals, which help to uncover how resonances of the transient waveform decay over time. Specifically, we use a derivative of the 13 Hz low-pass filter and a bandpass derivative of the difference between the 1 and 13 Hz low-pass filters. Finally, we apply a constant-Q Cepstral transformation on *each* of the aforementioned four transforms.

The constant Q transformation uses a filter bank with overlapping and logarithmically increasing bandwidths to break apart the frequency spectrum of the transient signal. After the filter bank, we apply a magnitude and log operation to turn multiplication of two systems in the frequency domain into addition operations. This has the effect of separating the “source” (an impulse or step into the plumbing system) from the “filter” (the physical bends and pipe lengths in the plumbing system). We then take the discrete cosine transform (DCT) of the constant-Q coefficients, which compacts harmonic structures down towards lower indices of the transform (commonly known as low-time cepstral coefficients). We truncate these coefficients (known as low-time *liftering*) before applying similarity algorithms. For more information on our constant-Q transformations, see Chapter 7 and Larson *et al.* (2010).

We use two similarity algorithms over the eight signal transformations: a matched filter and a Euclidean distance measure. The matched filter is an optimal similarity measure for orthogonal signals in the presence of white noise (North, 1943). Because our signals resemble decaying sinusoids, we can expect the above transformations to result in signals that are approximately orthogonal. The matched filter is used to compare the first four signal transformations, while the Euclidean distance measure is used for the four Cepstral transformations (given that the Cepstral space is already aligned, a matched filter type approach is unnecessary). A similar set of signal transformations and comparison algorithms were used in the original HydroSense work (Chapter 7). However, to ensure the approach works robustly with real-world data, we added the 4^{th} signal transform above (the bandpass derivative) and eliminated the *mean square error* measure because it did not improve performance.

After every {*s*,*v*} comparison has been made, we reinterpret the similarity scores as probabilities. For the matched filter comparisons, this is trivial as the matched filter already returns a similarity score between 0 and 1. For the real Cepstral transforms, we use Euclidean distance measures d_m between each transient in **S** and template in **V**, such that $f_{EucDist}(\hat{s}|\hat{v}) = e^{-|d_m|}$ (a common interpretation of Euclidean distance as a probability in log-space: Chen and Rosenfeld, 2000).

At this point in the algorithm we have an unknown transient *s* and the results of the four matched filter comparisons and the four exponential Euclidean distance comparisons (for every template in our library). To form a single template probability score, we multiply the comparisons of each template together. These scores are then grouped by valve (*i.e.,* all “kitchen sink open hot” scores are grouped together; all “bathroom sink close cold” are grouped, etc.). We then take the *argmax* over each valve grouping to find the probability that a particular valve is the originator of *s*.

Because we now have a single probability score for each valve, we can combine these with the probability of observing valve-specific features. These features are low dimensional vectors or scalars that are pre-calculated for each valve at a deployment site. In particular, we use two features: (1) stabilized pressure drop and (2) amplitude/resonance tracking; however, other features such as *damping ratio* and *time of day used* could be explored in the future. The stabilized pressure drop can be calculated by assuming that the transient is an underlying step function with three parameters: (a) time at which the step occurs, t_0, (b) magnitude of the step, A_0, and (c) region, T, where the transient has many high frequency components and cannot be modeled by a step. These parameters can be solved for (in the mean square sense) using linear regression with a "don't care" region. After regression, the stabilized pressure drop is the scalar value A_0. For resonance/amplitude tracking we assume the transient can be modeled well by a four pole system and we use an auto regressive model to estimate the pole locations. Each pole represents the strongest resonances and resonance magnitude that can vary between valves.

We train probabilities for these features by calculating the pressure drop and resonance values for all templates in our library and then using Gaussian kernel density estimation (KDE) (Bowman and Azzalini, 1997) to assign probability distributions to each valve in a non-parametric way. This results in a look-up table between feature observations and valve-level probability estimates. These probabilities are multiplied with the template probabilities to complete term (i). Note that when multiple pressure sensor streams are available, such as when two installation points are used, the probabilities for each stream can be multiplied together to form term (i). If we wish to use template comparisons *only*, we can simply choose the template with the highest probability. To incorporate with a language model, we use the best valve probabilities to enumerate the state space of a trellis in a bigram graphical model (where each valve is a separate state).

8.4.2 Term (ii): The Language Model

The *language model* assigns probabilities for possible valve sequences. This is performed using bigrams and is represented by term (ii) in eq. (8.2) (N represents the length of the sequence). Bigram analysis is commonly used in the statistical analysis of text to examine co-occurrences of words or letters. Here, our bigrams are groups of two sequential valve events; for example, *toilet open→bathroom sink valve hot open* comprises a single bigram. The language model consists of transition probabilities for every valve pair $\langle v_{n-1}, v_n \rangle$ and is trained by counting the number of co-occurring valve pairs in our library. These counts are smoothed using Katz smoothing, which is commonly used in speech recognition and works to assign a non-zero probability to every sequence (Chen and Rosenfeld, 2000). This is important for handling transition probabilities between two valves that rarely occur in our library.

Traditionally, language models use these transition probabilities to select the optimal word (valve) sequence from all possible word (valve) sequences. We maintain an *n-best list* of sequences using Viterbi-stack decoding (Chow and Schwartz, 1989). This allows us to dynamically reorder the most probable sequences as new valve events occur. Crucially, it also allows us to reorder based on secondary knowledge sources—particularly term (iii) and term (iv) in eq. (8.2).

8.4.3 Term (iii): The Grammar

Term (iii) describes a grammar, which is typically used to define a set of structural rules that govern the composition of sentences, phrases, and words in a given language. Here, our grammar defines the possible ways in which valve sequences can be constructed. Our grammar rules are: (1) an opening of valve v_x must be followed by a closing of valve v_x; (2) a valve's closure must be preceded by its opening; (3) and the temperature state of a valve must be consistent—*e.g.,* a *kitchen sink hot open* event cannot be closed by a *kitchen sink cold close* event. Rather than eliminating impossible valve sequences (such as a close before an open or an open with no close), we use a *soft grammar* which applies a penalty to any valve sequence that violates a rule. In this way, sequences which contain grammatical errors but have the likeliest probabilities from the other terms can still be selected as correct. The grammar is applied to each sequence in the n-best list, resulting in a set of *paired valve tuples* β. In eq. 8.2, the term f_p penalizes all unpaired valves (those not in β).

These paired tuples now bind together specific valve open and close events to form a full water usage event structure. For example, given the valve event sequence $v_1 \rightarrow v_2 \rightarrow v_3 \rightarrow v_4$ where v_1*=toilet open*, v_2*=bathroom sink open,* v_3*=toilet close, and* v_4*=bathroom sink close,* our pairing algorithm might link the two toilet events into $\hat{\beta}_1 = \langle w_1 | w_3 \rangle$ and the two bathroom sink events into $\hat{\beta}_2 = \langle w_2 | w_4 \rangle$. These linkages are critically important because they allow us to compute an additional feature set (described in term (iv)) that is dependent on knowing the beginning and ending of a water usage event. We note that the language model and pairing is a novel aspect of our system. The original HydroSense had no notion of either and thus could only identify individual valve events but not the relationships between those events.

8.4.4 Term (iv): Paired Valve Tuple Priors

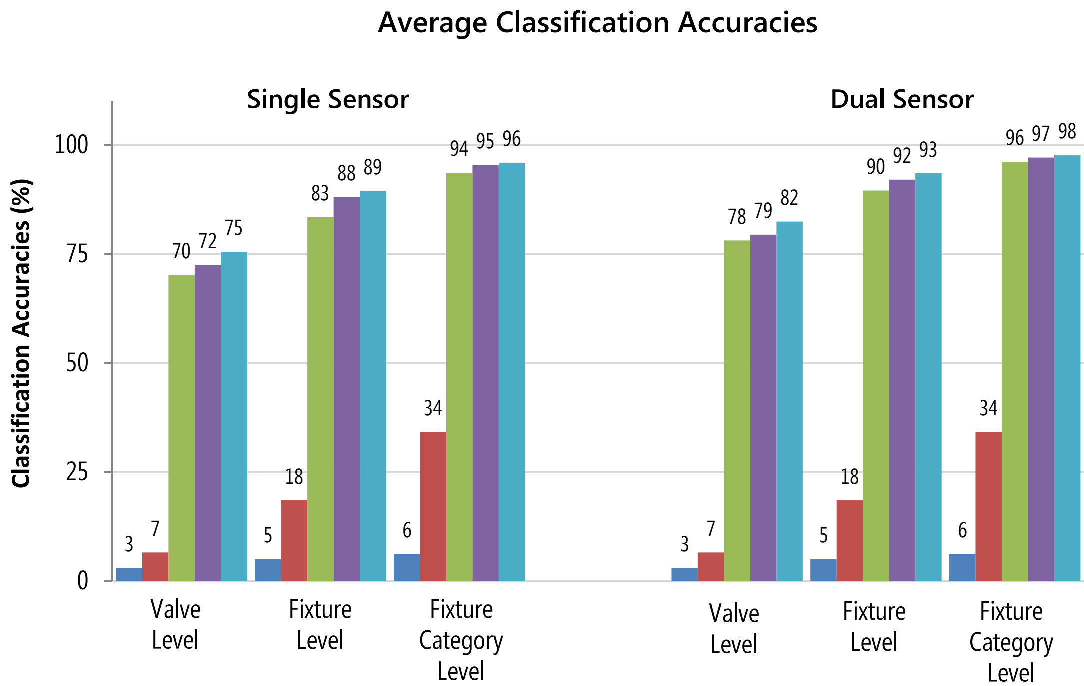
By pairing valve events, we not only have the ability to link open and close transients together but also to compute classification features, such as *water usage duration* and relative *estimates of water volume*, which are not possible without a pairing methodology. For every paired valve tuple in β, we compute *K* features over the entire water usage event, denoted as f_k in eq. (8.2). Similar to the *transient features* used in term (i), a probability density is calculated using KDE and the example water usage events in our library. For example, given a particular draw length for an unknown tuple, we can use the usage durations for all kitchen sinks in our dataset to lookup the probability that the usage event is a kitchen sink. Once all paired prior probabilities have been multiplied together, the n-best list is reordered and the likeliest valve sequence is chosen.

We use two paired valve priors selected experimentally using one week of data from each deployment site: *usage duration*, the amount of time the given valve pair is drawing water and *flow-trace max*, an estimate of the maximum amount of flow used over the duration of the event (a feature also used in flow-trace analysis: DeOreo *et al.*, 1996a).

8.5 ANALYSIS AND RESULTS

We compare the performance of three classification algorithms: a template classifier (term (i)); a classifier that adds a language model and grammar: *templ+LM* (terms (i, ii, iii)); and our full classifier *templ+LM+priors* (the complete eq. (8.2)). For baseline performance, we include *chance* and a *majority* classifier, which always selects the most likely result based purely on frequency. We were most interested in how the *templ+LM+priors* approach compares to the *template* approach. Additionally, we investigate the performance of each algorithm when using a single pressure sensor (hot or cold) versus dual pressure sensors. For the single sensor analysis, we chose the sensor (hot or cold line) that performed best. This was the cold line for all sites except for A2, where the majority of events were hot water use only.

To understand how the algorithms perform at different granularities, we conduct *valve* level, *fixture* level, and *fixture category* level classification. For valve level, the algorithm must identify the correct *fixture* responsible for the pressure transient, whether it is an *open* or a *close*, and its *temperature state* (hot, cold, or mixed). Fixture level ignores temperature state. Finally, for the fixture category level, we use the same categories as flow-trace analysis (*e.g.,* Mayer *et al.*, 1999). The algorithm must correctly classify open/close events as *bath, clothes washer, dishwasher, faucet, shower* or *toilet.* Note that the same models were used to train and test all three different granularities; however, temperature errors were ignored in the case of fixture and category level.



chance	3.0%	5.1%	6.2%		3.0%	5.1%	6.2%
majority	6.5%	18.5%	34.2%		6.5%	18.5%	34.2%
template	70.2%	83.4%	93.6%		78.1%	89.6%	96.2%
templ+LM	72.5%	88.0%	95.4%		79.4%	92.0%	97.1%
templ+LM+priors	75.5%	89.5%	95.9%		82.4%	93.5%	97.7%

Figure 8.10: Average classification results across the five deployment sites comparing *algorithm*, *single* vs. *dual* sensor, and different granularities (*valve, fixture, fixture category*).

We first focus on pre-segmented classification performance using data from a *single* pressure sensor. Figure 8.10 displays the results of a 10-fold cross validation experiment over the full five weeks of data using the three classification algorithms and two baselines. In general, the best performing algorithm is *templ+LM+priors*, which resulted in an average overall classification accuracy of 75.5%, 89.5%, and 95.9% for valve, fixture, and fixture-category level, respectively, across the five deployment sites. The best performing home, H2, resulted in 89.4%, 94.3%, and 98.4% classification accuracies. In contrast, the worst performing home, H1, resulted in 66.6%, 79.6%, and 91.0% accuracies because of the lack of cross talk between hot and cold plumbing lines and the logarithmic pressure falloff during usage. Surprisingly, the two apartments, A1 and A2, both performed reasonably well with a single sensor: 77.3%, 89.7%, and 95% for A1 and 78.7%, 94.3% and 96.9% for A2. This is despite the pipe length distance between the hot and cold lines in an apartment being much longer than in a house.

	M. Bathrm Faucet	M. Bathrm Toilet	M. Bath	M. Bath Diverter	M. Shower	S. Bathrm Faucet(s)	S. Bathrm Toilet(s)	S. Bath	S. Bath Diverter	S. Shower(s)	Kitchen Faucet	Dishwasher	Washing Machine	Other
M. Bathrm Faucet	84.9	0.8	0.7	0.1	0.1	5.8	0.0	0.0	0.0	0.1	10.2	0.2	0.1	1.0
M. Bathrm Toilet	1.8	93.3	0.4	0.4	0.2	4.5	0.8	0.8	0.0	0.0	1.6	0.2	0.4	3.6
M. Bath	4.0	0.9	79.1	2.1	2.6	1.0	3.0	5.0	0.0	2.0	1.8	0.3	1.9	21.8
M. Bath Diverter	4.9	1.8	1.4	81.6	4.5	0.0	0.0	2.3	7.0	2.3	3.6	0.0	0.0	0.0
M. Shower	3.7	2.0	5.2	0.5	80.7	3.1	0.5	0.0	0.0	3.8	3.5	0.0	0.3	1.0
S. Bathrm Faucet(s)	7.0	0.2	0.0	0.1	0.1	86.1	0.1	0.1	0.1	0.2	5.4	0.1	0.3	0.0
S. Bathrm Toilet(s)	2.0	1.1	3.2	1.1	0.0	0.2	91.0	2.7	0.0	0.0	1.5	0.0	0.0	2.0
S. Bath(s)	0.0	6.8	4.5	0.0	0.0	0.0	2.3	81.8	0.0	4.5	0.0	0.0	0.0	0.0
S. Bath Diverter	2.3	0.0	0.0	0.0	2.3	0.0	0.0	0.0	90.9	2.3	2.3	0.0	0.0	0.0
S. Shower(s)	0.0	0.0	0.0	0.0	2.1	6.4	0.0	0.0	0.0	89.4	0.0	2.1	0.0	0.0
Kitchen Faucet	4.9	0.3	0.1	0.0	0.0	1.4	0.0	0.0	0.0	0.0	93.6	0.5	0.1	0.9
Dishwasher	4.0	0.0	0.0	0.0	0.0	0.9	0.5	0.0	0.0	0.5	11.0	84.2	0.0	0.0
Wash. Mach.	2.1	0.9	4.2	1.0	2.1	1.0	0.0	0.0	0.0	0.0	1.6	0.0	81.0	30.1
Other	0.9	0.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0	5.1	92.7

Figure 8.11: A confusion matrix that averages the confusions for fixture-level *templ+LM+priors* classifications across deployment sites. Note that averaging makes it such that the percentages do not add to 100%.

To examine how events were misclassified, we calculated a confusion matrix for *templ+LM+priors* (), averaging the classification percentages at the fixture level across the five deployment sites. In general, classification accuracies are quite good—the most frequently used fixtures: kitchen sink, bathroom sinks, and bathroom toilets have an average classification accuracy of 90%. Confusions tend to occur within fixture categories (*e.g.,* between sinks) and between fixtures that are situated close together with respect to plumbing layout. For example, the faucet in the secondary bathroom is misclassified as the master bathroom faucet 7% of the time while the dishwasher is misclassified as a kitchen sink 11% of the time (dishwashers are only a small distance from kitchen sinks). Recall from Table 3 that the *other* category involves data from only one home (H1) and is for the laundry basin and refrigerator water dispenser, which were classified correctly 86.1% and 98.6% of the time. However, the *washing machine* was confused as a laundry basin 30.1%, which is visible in Figure 8.11—this confusion can be attributed to their valve's proximity in the plumbing system.

With regards to compound and collision events, the two language model-based algorithms tend to perform better than the *templ* algorithm (Figure 8.12). This is likely due to the transition probabilities of the language model and the paired valve priors in term (iv). Both reduce the weight placed on template-matching the distorted transient.

As expected, the addition of a second pressure sensor improves the overall classification accuracies for each algorithm and sensing resolution granularity: an average of 10% for valve level, 5.5% for fixture level and 2.1% for fixture category level across the three algorithms (Figure 8.10). The *templ* algorithm benefited the most from the addition of the second sensor. Similar to the single sensor, the *templ+LM+priors* algorithm performed the best with overall accuracies of: 82.4%, 93.5%, and 97.7% for valve, fixture, and fixture category levels. Because of the lack of cross talk between hot and cold pressure lines, H1 and the apartments benefited the most from the addition of a second sensor, especially for valve level classification (an increase of 9.5% vs. 3.1% for the other two sites). Two sensors also increase compound and collision accuracy by 5.3% and 4.4%. Finally, as noted in Table 8.1, the toilet and showerhead were replaced with low-flow equivalents in A1 approximately three and a half weeks into the deployment. After training on these new fixtures, we were able to correctly classify their usage despite being in the same fixture category and installed in the same location as the previous fixtures. For example, the new toilet was correctly classified 90.2% of the time and classified as the old toilet 8.2% of the time (we kept the old fixture templates in our database for all classification experiments).

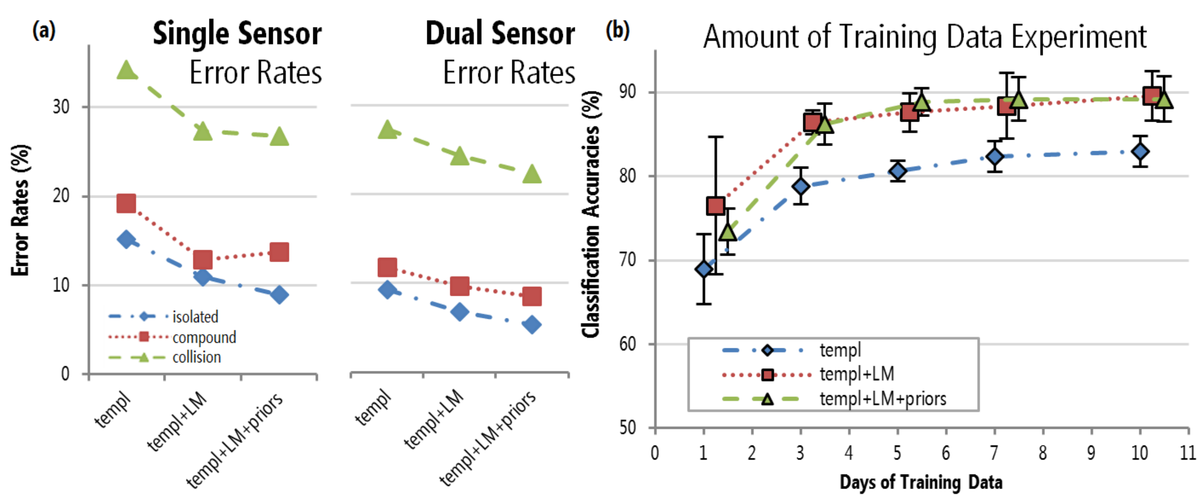


Figure 8.12: (a) The error rates for fixture-level performance broken down by algorithm and whether the error occurred on an isolated, compound, or collision event. (b) The results of our amount of training data experiment; 1,3,5,7 and 10 days were used to test a two week period. Note that we offset the data points slightly for each algorithm to improve the readability of the graph. Error bars reflect one standard deviation above and one standard deviation below the mean.

To test whether *templ+LM+priors* offered a significant overall improvement over *templ* (the approach used by the original HydroSense work described in Chapter 7), we conducted a three-way repeated measures ANOVA. We used the 10-fold classification accuracies as the dependent variable and *sensing resolution*, *number of sensors*, and *algorithm* (*templ* vs. *templ+LM+priors*) as within-subjects factors. Because we were only interested in the comparisons between the two algorithms, we report only main and interaction effects with *algorithm*. We found a significant main effect of *classification algorithm* ($F_{1,4}$=21.76, p=.010), indicating that *templ+LM+priors* improved performance over *templ*. No interaction effects with *algorithm* were significant, which means that two algorithms were not affected differently based on the sensing resolution or the number of sensors.

To investigate how the amount of training data impacts performance, we trained models with one, three, five, seven, and ten days of data. The amount of data is divided by days, not number of templates, as the language model requires contiguous blocks of events for training. All were then tested on 14 non-overlapping days. The results are presented in Figure 8.12b. Significant improvements in classification accuracy are seen with only a small number of training days. On average, *templ+LM+priors* outperforms *templ* by 4.5%, 7.4%, 8.3%, 6.9% and 6.2% as the number of training days increases from one to ten. Note that both of the LM-based algorithms perform better throughout training though the *templ+LM* algorithm slightly outperforms *templ+LM+priors* with minimal training because it does rely on trained probability distributions for priors.

8.6 DISCUSSION

This research is the first to use pressure-sensing to disaggregate *real-world* water usage. Using longitudinal data collected from ground truth deployments across five residences, we showed that a single pressure sensor was sufficient to classify pressure transients with accuracies between 76% and 96% depending on granularity (*i.e.,* valve, fixture, or fixture category). With two pressure sensors, the accuracies rose to between 82% and 98%. To achieve these results, we introduced a new type of water usage inference algorithm inspired by research in speech recognition. Unlike the original HydroSense work described in Chapter 7, this new algorithm is probabilistic and leverages a language model, grammar, and prior probabilities to better handle pressure transient variability and to increase robustness in the face of compound events and collisions.

Despite these advances, there are important opportunities for future work. Our current analyses used *pre-segmented* pressure transients (*i.e.,* the start and end of waveforms are marked by the ground truth labels). Working with pre-segmented events allowed us to focus specifically on analyzing the *discriminability* and *consistency* of real-world water usage pressure transients. As such, our results demonstrate an *upper bound* of classification performance for our particular feature set and approach. Overall classification rates will likely drop once segmentation is implemented because of segmentation errors. This could be especially true for apartments which, depending on the plumbing structure, can be particularly sensitive to noise from other units in the building.

With that said, the original HydroSense work segmented staged water usage data with 100% accuracy, so segmentation of real-world data should be possible. The key challenge will be properly segmenting compound and collision events, particularly in apartments with a much noisier pressure signal. We note that our Bayesian approach is amenable to many common speech recognition detection techniques such as keyword spotting. As such, the *classification* and *segmentation* tasks could likely be combined to make the algorithm more robust to sources of ambiguity such as transient collisions. Indeed, most optimal statistical signal processing strategies become sub-optimal after separating segmentation and classification, which means the classification algorithms presented in this chapter may need adjustment once incorporated with an imperfect segmentation scheme.

In terms of training, we evaluated the classification algorithms using real-world data for both training and testing. For practical end-user deployment, we might expect a small amount of *staged* training data per fixture. Future work is necessary to establish what will be the most effective staged training data for accurate classification of real-world data. For example, our current approach trains the language model and priors using data from the home where it is deployed. A more general approach could leverage usage patterns and priors (such as duration of use) across different homes, thus reducing system calibration. It may also be the case that certain fixtures, such as toilets and dishwashers, require less calibration because of more consistent transients. Furthermore, unsupervised learning approaches may allow detection of previously unknown fixtures. An interface to allow correction of misclassifications and training of the algorithm over time may also prove beneficial.

Finally, our work underscores the importance of conducting *longitudinal* evaluations *out in the wild* (as argued by others as well, *e.g.,* Rogers *et al.,* 2007). Although challenging and resource-intensive, such studies are critical in providing a sound scientific basis for the sensing work that we do in the Ubicomp communities. In our case, studying the real-world uses of water, rather than only staged experiments, uncovered crucial limitations of past approaches and allowed us to characterize general challenges for water disaggregation research.

8.7 CHAPTER SUMMARY

In summary, this research is the first to demonstrate that sensing pressure is a viable technique for inferring *real-world* water activity. We used *labeled* pressure stream data collected through five-week ground truth water sensor deployments across five sites to evaluate the performance of a new *probabilistic method* for inferring water usage from a single pressure sensor. To our knowledge, these ground truth deployments represent the most detailed investigation of residential hot and cold water usage (and their classification potential) ever performed.

In the next chapter we explore how a water sensor, like HydroSense, can be used to provide eco-feedback to residents about their water usage. In particular, we describe the design and evaluation of a range of eco-feedback displays that visualize fixture-level details on consumption from real-time disaggregated water usage data.

Chapter 9

Design and Evaluation of Eco-Feedback Displays for Fixture-Level Water Usage Data

Figure 9.1: In this chapter, we explore eco-feedback displays for *disaggregated* water usage data. We evaluate different visual designs informed by Chapters 4 and 6 as well as how the eco-feedback data should be accessed and where the displays may fit in the home.

In this chapter, we apply the design considerations and formative insights from Chapters 4 and 6 to the design and evaluation of a set of novel eco-feedback displays for household water consumption. These displays are also based on an underlying water sensing system like HydroSense (from Chapters 7 and 8) that can provide real-time, fixture-level water usage data (*e.g.,* Figure 9.1).

The displays themselves were created through iterative pilot testing and explore a range of points in the eco-feedback design space including data granularity, temporal granularity, and type of comparison (*e.g.,* to neighbors or demographically similar households). By creating a set of designs that target different points in the design space, we were able to compare the impact of these different design dimensions across a variety of subjective measures including perceived usefulness, understandability, and aesthetic. We evaluated these designs in an online survey with 651 respondents and through in-person interviews with 10 households (N=20 adult participants). In subsequent text, the survey is referred to as the *Display Evaluation Survey* and the interview study as simply the *Interview Study.*

The survey was designed to both quantitatively and qualitatively assess reactions and preferences to a range of designs presented in a controlled fashion. As the survey was conducted online, it was our intent to receive a large number of respondents in order to analyze trends in the response data. In contrast, the interviews were focused on understanding differences in perspective and preference for different water feedback designs *within members of the same household*.

The contributions of this chapter are threefold:

- A set of novel eco-feedback designs for water usage, which explore a broad set of dimensions and themes within the eco-feedback design space.
- Findings from a large-scale online survey, which carefully controlled the presentation of our designs to allow us to identify and uncover particularly promising designs and/or design elements.
- Findings from a set of household interviews, which explored a larger set of novel eco-feedback designs than the survey and did so within the interviewees' own homes. Consequently, we were able to not only derive more qualitative feedback about our designs than is possible through an online survey but we could also contextualize such feedback and explore how, if, and why the designs actually fit in domestic spaces.

This research not only has implications for those interested in designing water feedback systems but also, more generally, for those working in other areas of eco-feedback (*e.g.,* electricity or gas). In addition, some of our findings are relevant not just to designers and HCI researchers/practioners but also to those in the water industry involved in billing and consumer-facing website design.

9.1 DISPLAY DESIGNS

Based on the design space in Chapter 4 and the formative survey findings from Chapter 6, we created two sets of water consumption feedback displays. Displays in the first set were designed to isolate and examine a subset of the eco-feedback design dimensions introduced in Chapter 4 within the context of water usage. The dimensions examined here include data and temporal granularity, comparison, goal-setting, and measurement unit. Displays in the second set were created as design probes to target and provoke discussion around complex issues such as privacy, competition, motivation (*e.g.,* conservation versus cost), and household social dynamics.

For both design sets, the primary goal was not simply to evaluate a particular instantiation of a design idea but rather to study the reaction that it provoked and the general themes that emerged. As such, not all of our designs were technically practical. Instead, they were meant to explore different points within a large design space. Our primary intent was to evaluate *water* usage feedback specifically, but many of the designs and our design findings have implications for other sorts of eco-feedback.

The designs described in the following sections were evaluated in the *Display Evaluation Survey* and the *Interview Study*. In this section, we include all of the final designs used in *either* evaluation. For some of the design dimensions we explored design options through textual questions in the online survey without varying the visual display, which we note where appropriate. The evolution of some of the more complex designs can be found in Appendix D, while the final designs used for the interviews are found in Appendix I.

9.1.1 Isolating Design Dimensions

From the list of eight design dimensions in the eco-feedback design space presented in Chapter 4, we selected a subset (4) to explore in the context of water usage feedback displays. To pursue these explorations, we created one base design—a bar graph—that could be varied across various dimensions of interest. In this way, we could study how people reacted and responded to different variables in the design space with only one or a few changes to the look and feel of the interface. For example, we could show respondents a bar graph design that displays water usage by fixture type as well as a design that also incorporates temperate (hot and cold water use) information without fundamentally varying the design (Figure 9.2c and Figure 9.2d). We examined four aspects from the design space: *Data Granularity*, *Temporal Granularity* (called “temporal grouping” in Chapter 4), *Comparison*, and *Measurement Unit*. Our aforementioned base design had been iterated on via informal pilot testing and design critiques within our research group.

9.1.1.1 Data Granularity

Data granularity refers to the degree with which data is sub-divided or grouped. We explored three different levels of data grouping (Figure 9.2) (i) the *Individual Fixture View* displays water usage at each individual fixture (*e.g.,* upstairs bathroom toilet, downstairs bathroom toilet); (ii) the *Fixture Category View* displays water usage grouped by each *type* of fixture (*e.g.,* all toilets in the home are combined, all showers are combined); and (iii) the *Activity View* displays water usage grouped by activity rather than fixture (*e.g.,* cooking and cleaning, lawn watering, personal hygiene). The *Individual Fixture View* and the *Fixture Category View* could be implemented with current sensing technology (*e.g.,* HydroSense in Chapters 7 and 8); the *Activity View*, however, would require higher level machine learning models and, most likely, additional sensors in the home to detect and infer activities. For our investigations here, however, we ignored such technical challenges and focused instead on evaluating the *idea* of presenting water usage data grouped by activity.

Figure 9.2: The four *Data Granularity* views: the *Individual Fixture View*, the *Fixture Category View*, the *Activity View*, and the *Hot/Cold Breakdown View*.

We also examined interest and reactions to including temperature information in the feedback display via the *Hot/Cold Breakdown View* (Figure 9.2) Water heating accounts for 10-15% of the energy expenditure in the average American home (U.S. Department of Energy, 2001). Thus, hot water is not only more expensive but also has greater environmental impact through energy-based CO_2 emissions (see Weber and Matthews, 2008). Hot water is also interesting from a behavioral point-of-view because two heavy hot water uses—showering and laundry—can be changed via either curtailment or efficiency behaviors. For example, hot water use can be reduced by the installation of low-flow showerheads or a new, more efficient laundry machine (efficiency behaviors) or curtailment behaviors: shorter or less frequent showering, only doing laundry on a full load, and/or washing clothes on the cold water setting.

For the temperature design and for many others in the *Isolating Design Dimensions* section, we used the *Fixture Category View* as the base design. The *Fixture Category View* was selected because it was a clear, concise display with little visual noise. We used the same base design to maintain consistency throughout our evaluation.

9.1.1.2 Temporal Granularity

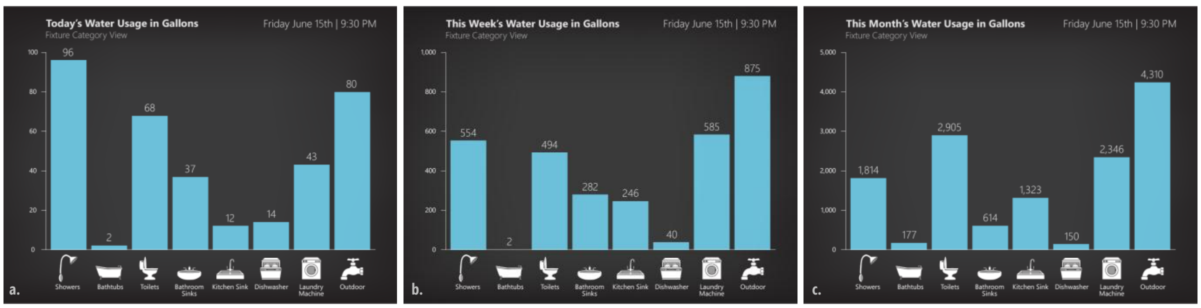


Figure 9.3: The three *Time Granularity* views: (a) *By Day;* (b) *By Week*; and (c) *By Month*. Recall that these are realtime displays that update immediately with water use so the displays show water usage so far today, this week and this month.

Temporal granularity refers to the time window with which data is calculated and presented. We explored three different temporal granularities: (i) *By Day*; (ii) *By Week*; and (iii) *By Month*—see Figure 9.3. Each time window presents a different tradeoff between the ability to observe small, immediate updates versus the ability to observe general usage patterns. For example, some water usage activities such as using the laundry machine or lawn sprinkler may not occur every day. The impact of these activities on consumption is more clear in a *By Week* view or a *By Month* view than in a *By Day* view. In addition, most of us are used to thinking of our home resource consumption in terms of months rather than days as this is the traditional time window used in billing. So, we thought that users might prefer a month-view of their water usage data for consistency and billing purposes.

9.1.1.3 Comparison

As noted in the eco-feedback design space chapter, comparison is, perhaps, the most fundamentally important part of any feedback display. By presenting comparison data, a display can reveal what is typical or normal usage. In this way, comparisons can actually diminish the importance of understanding particular measurement units (*e.g.,* what is a gallon?) in favor of emphasizing whether usage is more or less than usual. Chapter 4 covers a large spectrum of the possible comparison targets that one could use as a basis for comparison such as comparing to past performance or the performance of others. Within each of these comparison targets, there are a variety of possibilities: for example, in comparing with oneself—or in this case with one's own household—the comparison could be based on various temporal granularities of data (*e.g.,* a daily or weekly average for example) as well as different time windows of data (*e.g.,* this daily average is based on the last 30 days of data). Thus, the complexity and, possibly, motivating influence of a comparison is dependent on *how* comparisons are calculated and *how* this calculation is presented to the user.

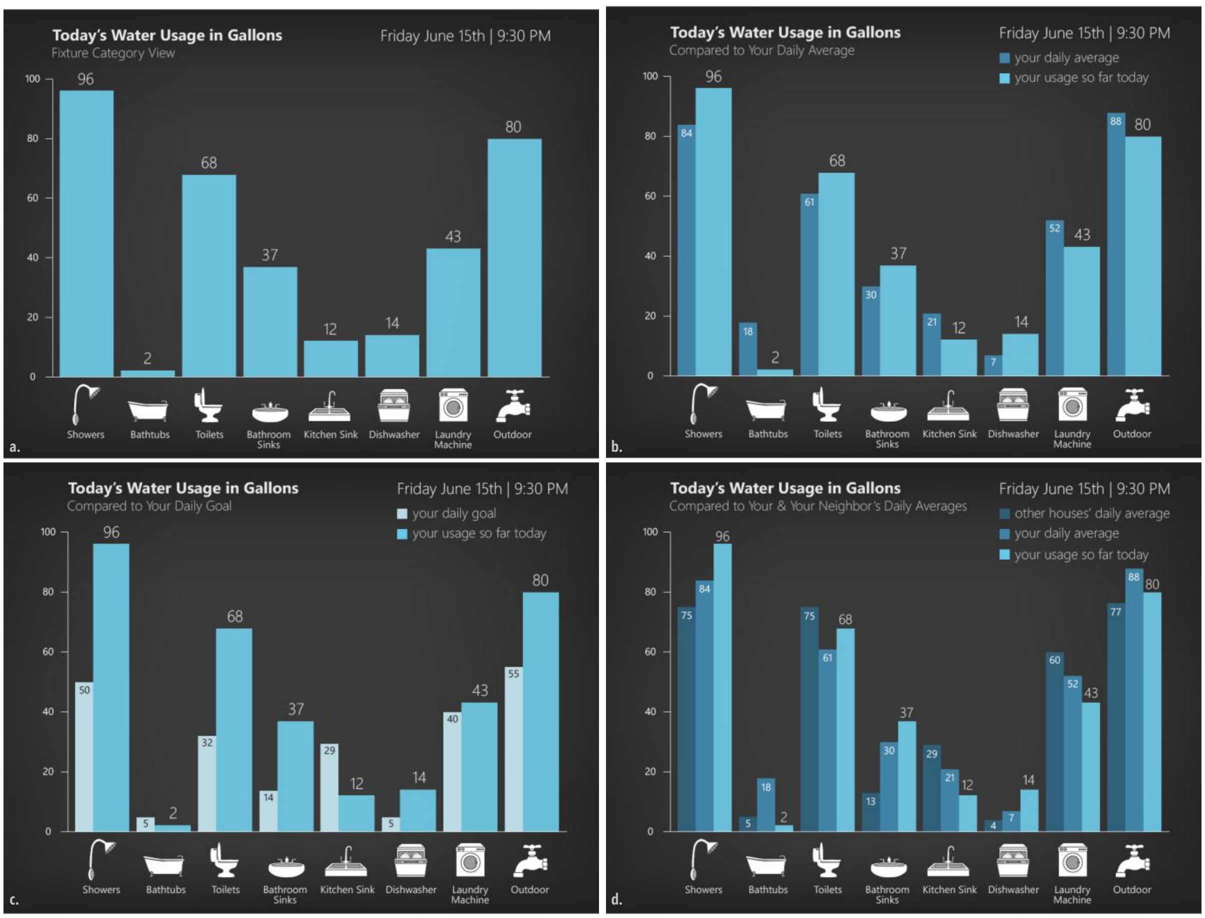


Figure 9.4: The *Comparison* views: (a) the baseline *Fixture Category View*, (b) the *Self-Comparison View* comparing current usage to a daily average, (c) the *Goal-Comparison View* comparing current usage to a daily goal, and (b) the *Self- and Social-Comparison View* comparing current usage to a daily average and the daily average of other households.

For our purposes here, we wanted to focus both on how to best represent comparison data in a visual bar graph display as well as to investigate what sort of comparisons people are interested in for water usage data. Towards the first goal, we conducted pilot testing with 17 participants to select and iterate on a visual technique for presenting comparisons. Our focus, primarily, was in exploring methods to visualize comparison values along with current values for each bar in the bar graph (*e.g.,* using tick marks, lines, or an additional bar in a bar chart). We also investigated whether and how to depict water use exceeding the comparison value. Full details of the pilot tests are found in Appendix C. Overall, from our pilot tests, we found that participants felt that the comparison value displayed as a second bar alongside the current value bar was the most intuitive of the options; however, having two bars of equal visual weight was deemed distracting. Thus, our final comparison design, shown in Figure 9.4b uses a two-bar visual design where the comparison value (the second bar) is smaller in size and darker in hue than the current value bar.

Self-Comparison

In terms of investigating *what* to compare, we investigated self-comparison, social-comparison and comparing to goals. For self-comparison, we presented only one visual scenario—the ability to see daily averages next to current usages for each fixture type (Figure 9.4a). This scenario was selected because of its simplicity. In pilot testing, we explored using other values for self-comparison including medians, average values at the *current time-of-day*, daily averages constrained to the last few weeks of data, and daily averages from a 30-day interval from the *previous year*. However, these calculations were not well understood and provoked frustration rather than constructive feedback on the self-comparison concept. The need to ensure that the displays were simple and easy to understand was particularly important given our survey-based evaluation method—respondents would likely spend but a few seconds thinking about and looking at each design. For designs that were overly confusing, a respondent could simply give-up in frustration preventing us from using their data in our analysis. Thus, much of our pilot testing focused on eliminating confusion and simplifying our designs in order to prepare them for the survey evaluation. We return to this issue in the findings section.

Goal-Based Comparisons

Comparing to goals is a unique form of self-comparison where instead of using past performance as the comparison point, a specific goal target is set (*e.g.,* “we want to take 12 gallon showers” or “we only want to water our lawn once a week”). These goals can also incorporate past usage data: “we want to use 5% less water than usual.” For goals, we not only asked about whether people were interested in setting water usage related goals for their household but how these goals should be set (see Consolvo *et al.*, 2009 for a discussion of goal-setting considerations for persuasive technology). In particular, we explored the following goal-setting scenarios in the online survey:

- Manually set by a member (or members) of the household
- Automatically set by the display system to be 5% less than my daily average
- Automatically set by the display system to the water usage amounts of my most water efficient neighbors
- Automatically set by my water supplier (*e.g.,* a public utility)
- Automatically set by my local government

As with self-comparison, we used a single visual design to portray the overall goal-based comparison concept and then textually described the above scenarios.

Social-Comparisons

Finally, the last type of comparison that we explored was social comparison. Here, we investigated whether people were generally interested in comparing their household water usage to others. We also examined particular scenarios such as comparing to geographically proximal versus demographically proximal neighbors. This latter type of comparison has been met with great success in the normative graphs on OPower bills (Laskey and Kavazovic, 2011). Again, we used a single visual design and textually described the scenarios below:

- The average of other households that are geographically close to my house (*e.g.,* my neighbors)
- The average of other households that are demographically similar to my house (*e.g.,* houses of similar size with the same number of occupants)
- The average of other households that are conservative with water (*i.e.,* water efficient households)
- Households of family or friends that I choose
- The average of other households in cities across my country
- The average of other households in cities across the world

In addition, we also asked a privacy-related question. Specifically, we inquired about the respondent's comfort with sharing their own household's water usage anonymously to enable these sorts of comparisons.

9.1.1.4 Measurement Unit

Measurement unit refers to the metrics used to measure and present usage. For water, this could include *volume-based measures* like CCFs, gallons, or liters or *flow-rate measures* such as gallons- or liters-per-minute. Given that many people pay for their water supply, one might instead emphasize

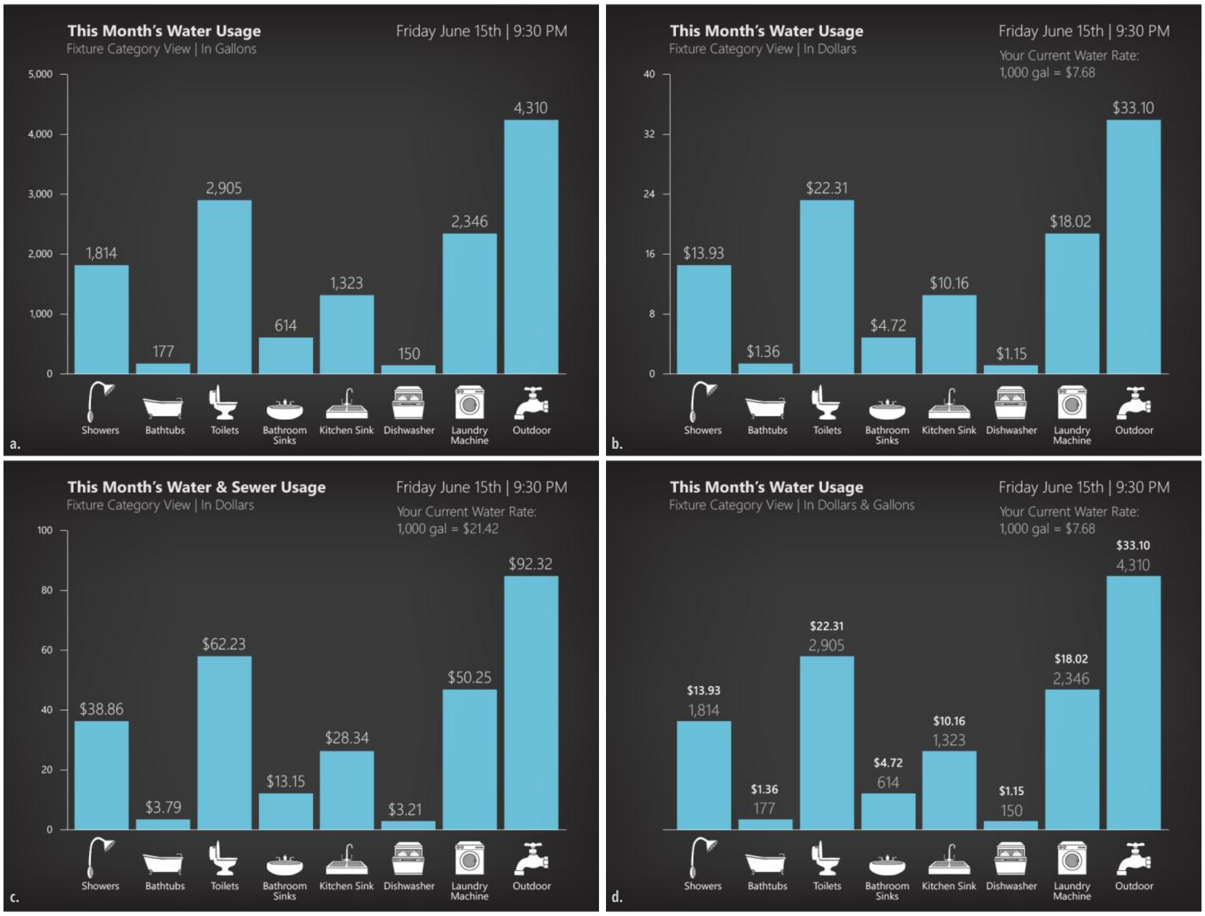


Figure 9.5: The *Measurement Unit* views: (a) the *Fixture Category View* by gallons, (b) by water cost, (c) by water and sewage cost, and (d) by gallons and water cost. Note that the display time window is by month and that it is currently the middle of June (the 15th). The y-axis was removed in (d) to reduce clutter and eliminate the need for a secondary y-axis on the right side of the graph, which was found to be distracting and confusing in pilot testing.

cost—*e.g.,* the cost per day, week or month of water usage. With disaggregate water consumption data, one could even present the cost per day, week or month of specific activities such as showering. Finally, the fourth common measurement unit as noted in the design space chapter is an equivalance or metaphorical unit. These types of measurement units are designed to make usage amounts more understandable and/or provocative. For water, this might mean creating an equivalence between the total amount of water used for the day and the number of toilet flushes required to reach this amount (*e.g.,* your household has used 213 gallons so far today, which is equivalent to 133 toilet flushes). Unlike energy, water has a myriad of common, everyday tangible manifestations that one can rely on for equivalence units—such as a one gallon milk jug or a five gallon water jug. These have strong visual associations making them conducive to serving as metaphorical units.

In the *Display Evaluation Survey* we examined gallons and cost as measurement units (Figure 9.5). In the interviews, we also explored a variety of metaphorical units in various designs. These are discussed in the *Volumetric Displays* subsection of *Design Probes.*

9.1.2 Design Probes

We move now from exploring specific design dimensions to, instead, exploring interfaces that integrate multiple dimensions within the same visual frame and are meant to be more provocative than the previous designs. The *Design Probes* were meant to explore various points in the large design space around water usage feedback and to elicit reactions around various underlying themes such as privacy, competition, motivation, and household social dynamics. Many of the design dimensions discussed above and in the eco-feedback design chapter are intergrated into these design probes.

We created seven design probes in all: *Time-Series, Spatial, Per-Occupant, Aquatic Ecosystem, Rainflow, Geographic Maps,* and *Volumetric*. The first three (Time-Series, Spatial, and Per-Occupant) were evaluated in the *Display Evaluation Survey*. In the interviews, we evaluated all seven. We briefly describe each in turn.

9.1.2.1 Time-Series

Time-series visualizations are, by nature, good at presenting trends, which allow users to determine general patterns in usage. For water consumption, there are three major temporal trends: time of day, day of week, and season. For time of day, there are generally three peaks of water usage: a sharp spike in the morning and two other peaks that correspond to dinner time and bedtime (see Chapter 6). For day of the week, residential water consumption can increase on the weekends with chores (*e.g.,* laundry, gardening, and lawn watering) and because people spend more time at home. Finally, in many climates, the summer is the highest season of use as people increase the frequency and amount of outdoor water usage for lawn and garden watering and other activities (*e.g.,* washing the car). We were interested in creating displays that revealed these sorts of trends and allowed people to observe differences in their own patterns across various time windows.

Depending on the time window of focus, different usage patterns are more immediately accessible. For example, a time-series line graph showing water activity during the day can make it easy to

Figure 9.6: The *Time-Series* views include: (a) a per-day view that shows the rate of which water is used (top, gpm) along with a cumulative view of this consumption (bottom, gallons)—note the comparison-tick on the cumulative graph, which reveals the typical water use amount at the current time of day; (b) a per-month view over past year that uses a stacked-line graph to show longitudinal disaggregated water use patterns—again, the comparison tick reveals typical use at that the current time in the month (June); (c) a view which combines (a) and (b); and (d) a disaggregated per-day view that shows water usage rates by fixture type along with a total. The combined view (c) was evaluated in the *Display Evaluation Survey* and the others were evaluated in the *Interview Study*.

determine *what* consumed the most water and *when* (Figure 9.6a). A graph showing a year's worth of usage, however, is much better for determining whether a household's use is decreasing or increasing and if the household is using less than the previous year over the same period (Figure 9.6b). These time windows also have different implications for privacy. For example, a time-of-day (*e.g.,* Figure 9.6a and d) view makes it easy to see when people get up in the morning, how long their showers are, when they leave and get home from work and when they go to bed. This could be perceived as intrusive or potentially create conflict in the home. We were interested in exploring whether these sorts of issues arose in our survey and interviews—in other words, do people realize or think about the implications of these water usage feedback systems *beyond water conservation*?

To make this more concrete, imagine a scenario in which a mother notices water usage at 12:30PM on a school day in her son's downstairs bathroom (which would be easily viewable in a display like that shown in Figure 9.6d). In this way, the display is revealing information not just about consumption but also about various activities and trends in the home. This information could have unintended consequences. In our scenario, it appears that the son has just skipped part of the school day, which is observable solely by examining water use activity visualized in the display. This sort of observation, however, is much less salient if not impossible to see in the per-month visualization. So, there is clearly a tradeoff between awareness of water usage patterns and potential for invasiveness. It is not just that a smaller time window of data could be more revealing but the way in which that data is presented (*e.g.,* a bar-graph view rather than a time-series view over the same time window could potentially reveal much less invasive information). Many of these issues exist for the other Design Probes as well.

For the survey, we evaluated Figure 9.6c. The interviews included all four designs shown in Figure 9.6.

9.1.2.2 Spatial

In their formative work exploring electricity feedback in the home, Riche *et al.* (2010) note how occupants draw relationships between locations in their home and activities. They suggest that floor plans are common when representing homes and afford an easily understood mapping between place and activity. Consequently, they recommend spatial-based presentations of electricity feedback in the home, particularly for feedback that disaggregates at the appliance- or device-level. We were similarly interested in exploring the affordances of floor plans and space for presenting water usage feedback. Unlike with electricity where there are electricity-consuming devices and/or appliances in each room—there are only a few rooms in a home that use water: namely, bathrooms, kitchens, laundry rooms, and outdoor spaces. So, perhaps, reactions to the spatial-based design will differ.

With our spatial-based designs, we were interested in exploring whether the information felt more intuitive and understandable than other presentations of the information (which would agree with Riche *et al.*'s findings for electricity). We were also interested in whether people perceived a privacy risk with a room-based view because particular activities (or lack of activities) could become clear. For example, depending on the data presented in the spatial-view, *where* and *when* people are in some rooms may become visible as well as particular hygienic practices. For instance, whether or not bathroom faucets were used after toilet flushes (*i.e.,* "did you not wash your hands after going to the bathroom?") or whether or not someone bathed/showered that day (*e.g.,* "Mom, Jimmy didn't shower today!!!").

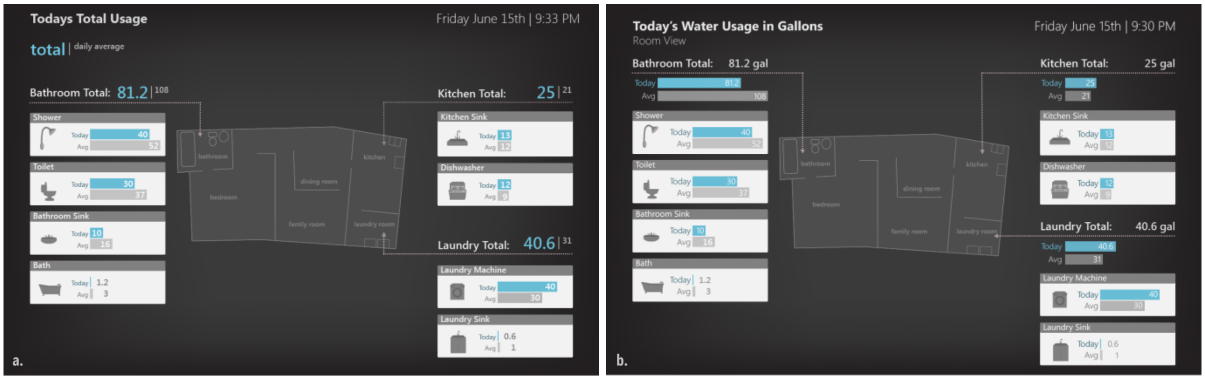


Figure 9.7: The *Spatial* views. Both views provide small bar graphs that show fixture usage so far today as well as daily averages. The view on the right, which was used in the *Display Evaluation Survey*, includes these bar graphs for the room as well.

In pilot testing, we found that people did not like the inclusion of timestamps, which allowed users to determine when a fixture was last used because it felt overly invasive. We also found that a single-bar comparison visualization technique was not nearly as well understood as a two-bar comparison even though a single-bar approach greatly reduced visual clutter (similar findings were noted in the Comparison section above). Our final design presented current usage data by fixture and by room along with comparison information for both (Figure 9.7).

9.1.2.3 Per-Occupant

The per-occupant display shows water usage broken down by user rather than just by fixture. The per-occupant view, perhaps more than any other, allowed us to specifically explore particular themes of interest including competition, accountability, blame, and privacy. In terms of its technological feasibility, one could argue that activity-recognition technology is progressing towards being able to track this sort of data (*e.g.,* using depth cameras for activity and identity recognition: Shotton *et al.,* 2011). However, we were not concerned with the practicality of this display but rather the reactions that it elicited. Of all of the designs, we expected this one to be the most provocative and polarizing—in fact, it was designed to be this way.

We were particularly interested in investigating if/how notions of competition would arise from looking at these displays and if people would be concerned about how much information was revealed about their daily patterns and routines. In addition, as per-occupant displays have not been explored before for eco-feedback in the home, we wanted to investigate whether people were generally interested in the concept.

In early designs, we specifically delineated between *personal usage* and *communal usage* (*i.e.,* usage that involved household chores like dish washing, laundry, or lawn watering). Note, for example, in Figure 9.8a where you can see that Mom and Dad use the most water in the family but much of this is due to communal usage (column titled "Communal Usage"). However, although this distinction came up in our formative water use surveys described in Chapter 6, we found it difficult to depict in a simple and easy-to-understand manner. Thus, we ended up dropping it for our final design used in the *Display Evaluation Survey* (Figure 9.8d).

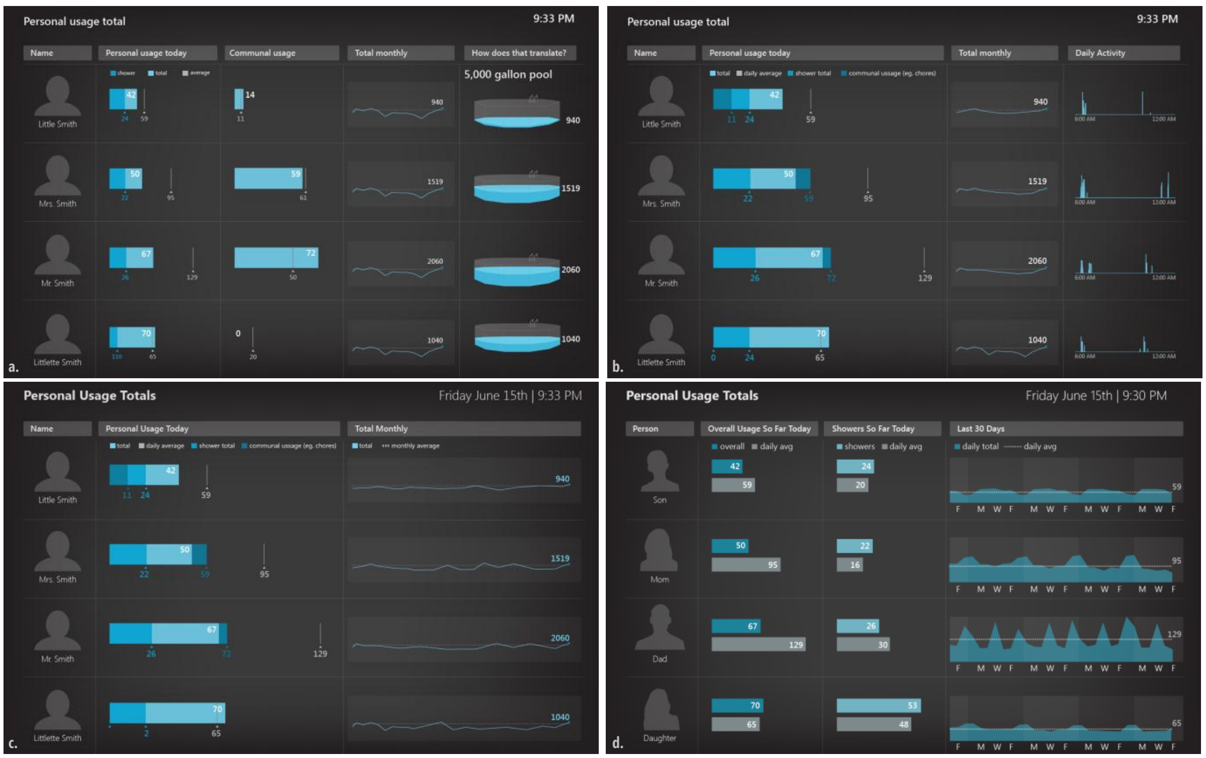


Figure 9.8: The *Per-Occupant* views. The first three variations (a, b, and c) include notions of *personal* vs. *communal* usage in the household (to account for water use that benefited the entire household, *e.g.*, laundry). This distinction was perceived as confusing in pilot testing. Design d was selected for the *Display Evaluation Survey* and shows overall water usage and shower usage with daily averages along with the last 30 days.

9.1.2.4 Aquatic Ecosystem

The most abstract and arguably most ambient of our displays is the Aquatic Ecosystem (Figure 9.9), which uses fish and plant life to depict water usage information in an *artistic* and *ambient* manner. In this way, the Aquatic Ecosystem is similar to the evolving ambient mobile phone display for transit activities in UbiGreen (Chapter 5 or the Fish'N'Steps display in Lin *et al.,* 2006). Here, the focus is not on presenting raw data in a functional manner but rather to use sensed water usage to effect an outcome in an ongoing narrative—just as we did with sensed transit and the tree and polar bear storyboards.

In addition, unlike all the other displays, which focus on tracking *consumption*, the Aquatic Ecosystem focuses on tracking water *savings* and meeting water saving goals. These goals may be simple—*e.g.,* reduce overall water use by 5% or outdoor water use by 10%—or more complex—*e.g.,* take shorter showers five days in a row or only use the laundry machine on the cold/cold setting for the next 10 washes. These goals could be manually defined or automatically set by the system based on water usage areas that receive excessive use or both.

Figure 9.9: The *Aquatic Ecosystem* is a "live" and "organic" reflection of water usage in the home. As water saving goals are reached, the ecosystem evolves in different, positive ways. In this case, once a water savings goal is met, "Frank the Fish" meets a new mate "Frannie the Fish." After subsequent goals are met, the ecosystem continues to evolve—*e.g.*, Frank and Frannie have children, new vegetation grows, or new fish arrive.

When goals are met, the ecosystem evolves in a positive manner—for example, by adding more vegetation to the bottom of the waterbed or adding a fish to the display. We did not explore punishment scenarios—*e.g.,* having water levels lower with sensed overuse or fish or plant life dying—as past work has questioned the use of punishment in creating long-term motivation (Consolvo *et al.*, 2008). The key design goal for us was to create a positive, visually attractive and compelling *ambient* display of water usage that could appeal to children, those who are less "data-centric," or simply those that wanted a more fun, playful display.

Given the unorthodoxy of this display and the explanations required to understand it, this display was not evaluated in the survey. Instead, we used this display and the narrative described in Figure 9.9 in our interviews. Given the different demographics and age groups within many households, we were particularly interested in exploring how this display might appeal to children as well as parents. We were also interested in investigating the use of *gamification* strategies in our design (see Chapter 4 for more information on gamification).

The Aquatic Ecosystem also has an interactive component where users can touch fish—who either follow the user's finger or swim away depending on simple behavioral models programmed into the design.

9.1.2.5 Rainflow

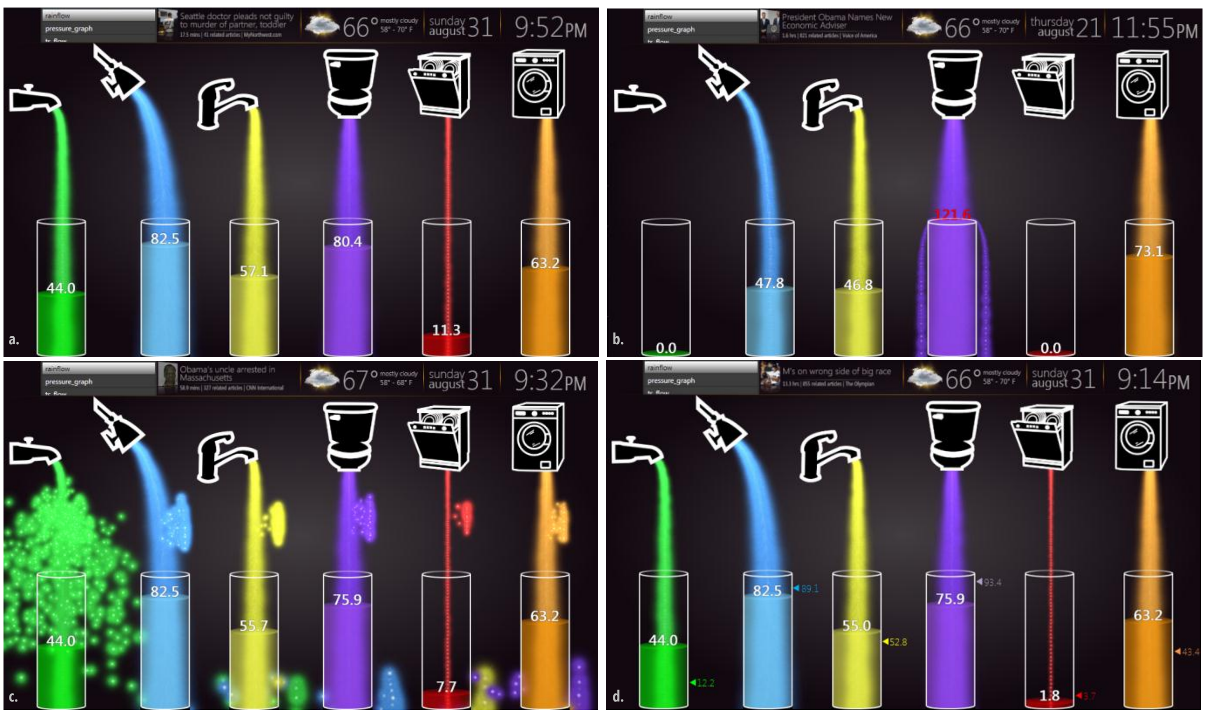


Figure 9.10: The *Rainflow* design. A particle system is used to simulate liquid, which flows out of the fixture type according to the amount used during the time period of interest (day, week, month). The cylinders at the bottom similarly fill up to represent the volume used—*i.e.*, the cylinders are stylized bar graphs. Given that the cylinders have a max capacity, they can overfill as depicted in (b). The display is also interactive. The water flows can be touched and played with (c) and the average and goal lines can be toggled on and off—average tick marks are shown in (d).

In a similar spirit to the Aquatic Ecosystem, Rainflow visualized water usage in a slightly more playful and fun manner than the other designs (Figure 9.10). Rainflow is a stylized and more ambient version of the *Fixture Category View* bar graph. Water flows out of the fixture icons at the top of the display and into containers at the bottom of the graph, which fill according to use. Thus, the fill amount in the container is like a bar in a bar graph. In addition, if water usage for the time period of interest (day, week, or month) exceeds a predefined level, the container overflows (Figure 9.10b, the toilet). Finally, like the Aquatic Ecosystem, the user can interact with the display—not just to acquire more information—but for playful purposes (*e.g.,* the user can run their hands through water streams and bubbles/water droplets fly out).

9.1.2.6 Geographic Maps

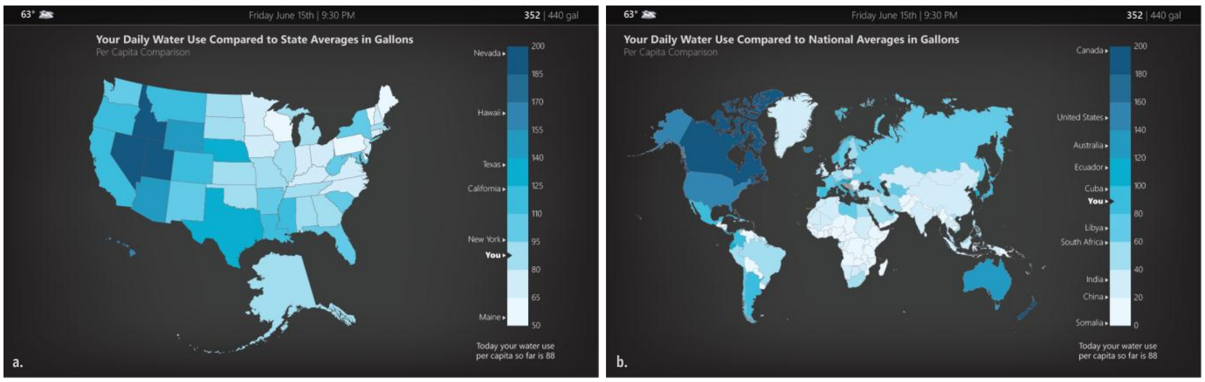


Figure 9.11: The geographic map displays show current household usage compared to averages (a) across the US and (b) the world. Note that the information depicted in these displays is accurate and taken from Kenny *et al.* (2005) and Gleick *et al.*, (2008).

In the Formative Water Survey, we found that just 2.3% of respondents who receive and pay their water bill have social-comparison information and yet 66% stated that they would be interested in it. So, in addition to the comparison displays shown in the *Isolating Design Dimensions* section, we also created two geographic map based displays that compare the household's current use to average use around the US (Figure 9.11a) and the world (Figure 9.11b). These were examined in interviews only (Figure 9.11).

9.1.2.7 Volumetric/Metaphorical Displays

As noted in the *Isolating Design Dimensions* section, water is a much more tangible resource than electricity. It can be felt, tasted, and touched. In addition, there are various metaphors that one can draw upon to make water use more understood (*e.g.,* gallon jugs). With the Volumetric design probes (Figure 9.12), we were interested in whether people found these sorts of designs intuitive or useful—whether they prefer them over bar graphs and if they provoke a different kind of reaction. In particular, do people get a better sense of how much water we use in our homes from looking at these displays? Do they provoke a feeling of "awe" or "guilt?"

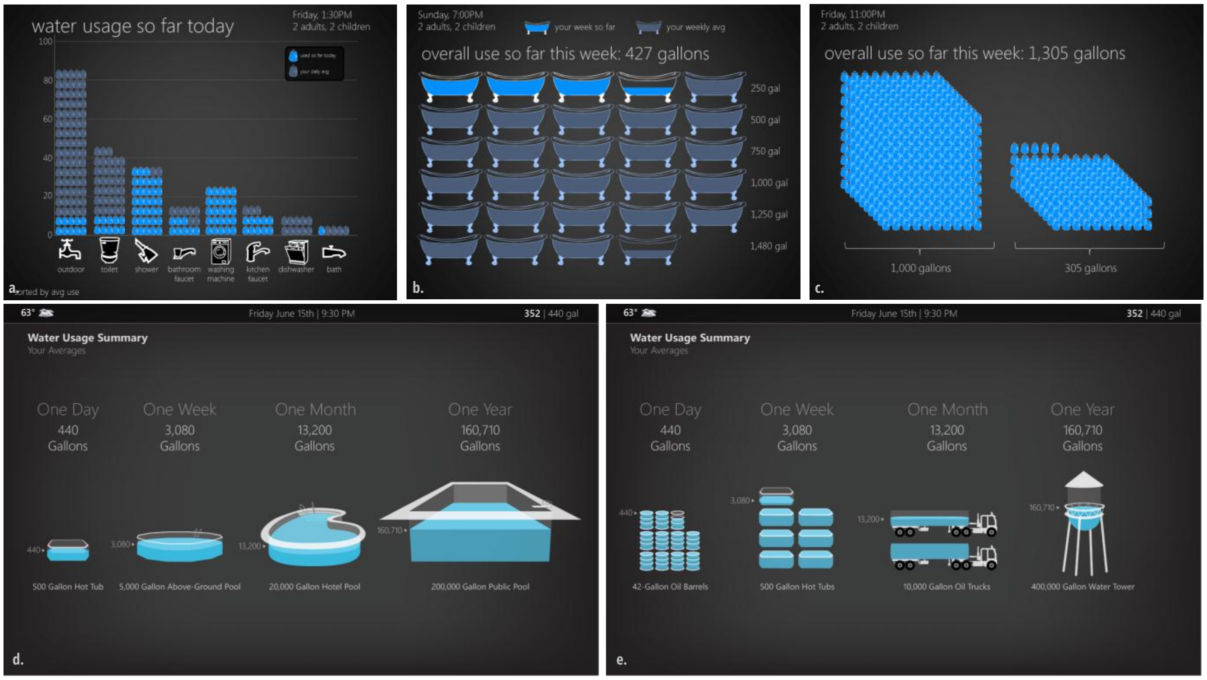


Figure 9.12 The *Volumetric* views. (a) A volumetric-based bar graph using one gallons jugs—the bright blue jugs represent current use and the darker jugs represent daily average. (b) An overall consumption this week visualization using 50 gallons bathtubs to depict use; again bright blue color represents so far this week and darker color represents average. (c) Similar to the previous display but using one gallon jugs instead of bathtubs and does not include comparison. (d) A water usage summary view showing average daily, weekly, monthly and yearly usage through the use of different sized pools from a 500 gallon hot tub to a 200,000 gallon pool. (e) Similar to the previous view but using other types of objects including a 42 gallon oil barrel, a 500 gallon hot tub, a 10,000 gallon oil truck, and a 400,000 gallon water tower.

9.2 DISPLAY EVALUATION

To evaluate the displays, we conducted two studies: an online survey of 651 North American respondents and 10 in-home household interviews with 20 adults. Our goal was not only to evaluate the specific designs themselves (*e.g.,* what levels of temporal granularity are considered useful and why?), but also to explore richer contextual themes surrounding the designs and potential use of the displays.

9.2.1 Online Survey Study Method

The survey was split into two parts. The first part evaluated a subset of the designs that isolated options within each of several design dimensions, including: data granularity (*e.g.,* by fixture type or individual fixture, hot and cold water usage), time granularity (*e.g.,* day, week, month), self- and social-comparisons, and goal-setting. The second part of the survey explored three of the design probes: the time-series view, room-based view and per-occupant view. These design probes were meant to elicit more complex issues and thoughts surrounding eco-feedback displays, such as privacy and household dynamics.

The results from this evaluation can help isolate particularly promising design elements and identify information that is particularly important to include in water usage feedback designs. In addition, the design probes are useful to begin teasing out tensions that exist between information and privacy, communal versus personal water use, and the perceived importance of time in contextualizing feedback.

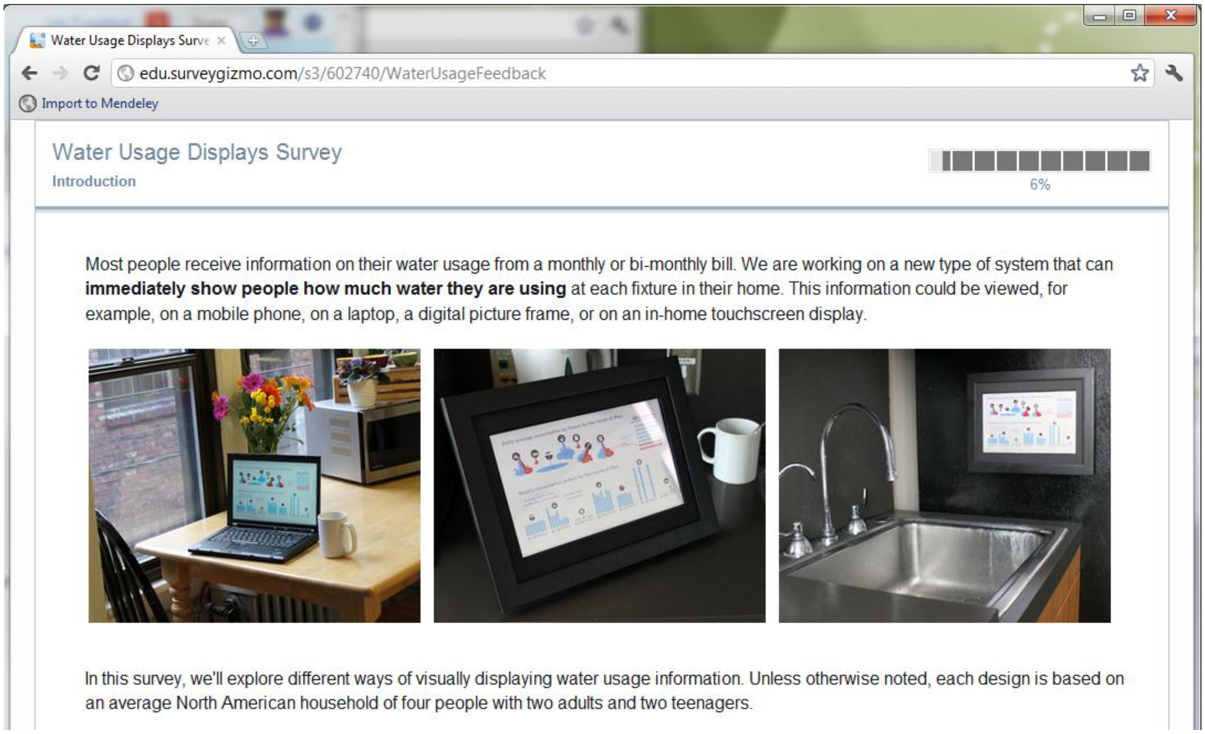


Figure 9.13: The introduction to the water usage feedback survey shown just after the consent form. We begin by describing our water usage feedback system and differentiating it from traditional forms of water feedback (*i.e.*, bills). We make three important points: (1) that our system provides real-time feedback about where and how much water is being used in the home; (2) that this information can be accessed on a variety of devices some of which are shown in the images; and (3) that the survey itself is focused on exploring different ways of displaying water usage information, which is based on an average North American household of four people with two adults and two teenagers.

The method of the Display Evaluation Survey largely followed that of the Formative Water Survey in terms of the hosting site (SurveyGizmo), participant recruitment, randomization of questions, and strategies to improve answer quality. Since the Display Evaluation Survey took longer to complete, we increased the amount of the random drawing from a $50 Amazon gift certificate to $100. We only describe key methodological differences between the two surveys here. The details common to both surveys' methods can be found in Chapter 6.

Upon starting the survey, respondents first answered a series of demographic questions and were introduced to the notion real-time water usage feedback (Figure 9.13). The two main parts of the survey followed: (1) isolating individual design dimensions and (2) evaluating the design probes. All survey questions and displays can be found in Appendix E.

9.2.1.1 Technical Details

Since the water usage feedback designs were the primary focus of our questions, we had to develop a mechanism to present these designs in a clean and simple manner. Ideally, respondents would be able to view and inspect images of our designs and compare them to one another with little-to-no scrolling. The challenge here though is that the online computing eco-system is rich and diverse—there are not only a variety of browsers but also devices with varying screen sizes. We needed to accommodate all of them. We were particularly concerned about laptop screen sizes because of their lower resolutions making it difficult to present more than one design within a viewable window.

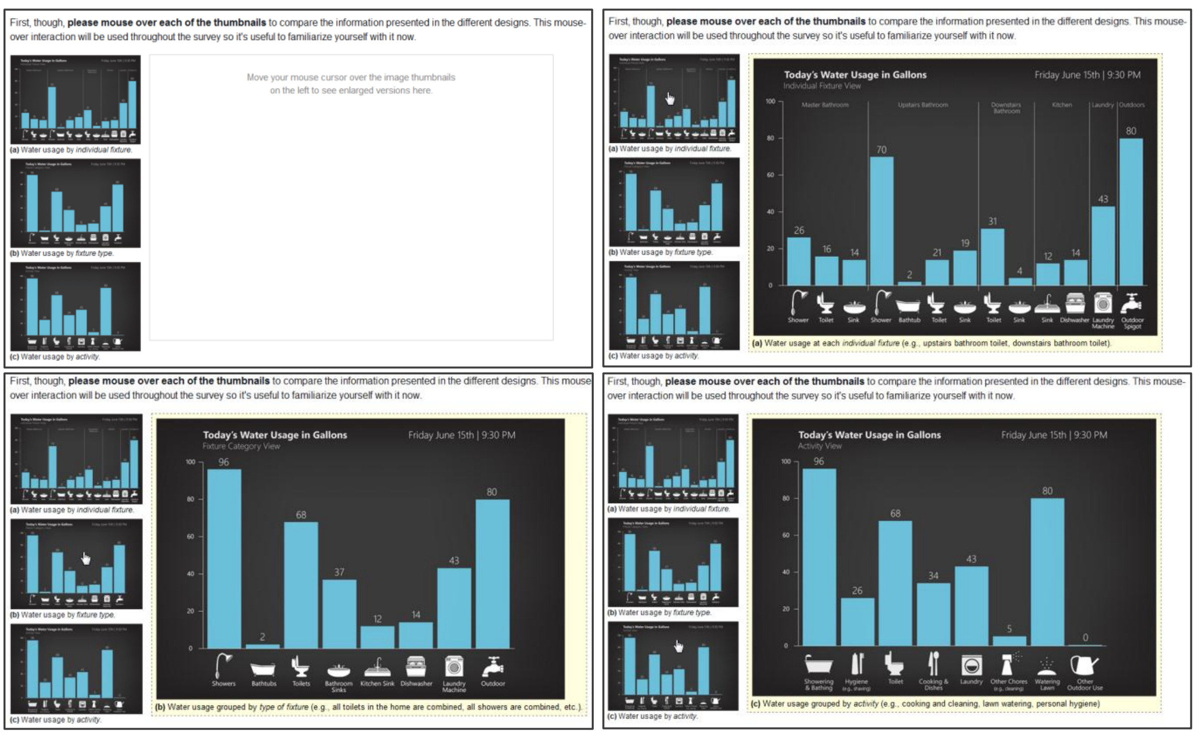


Figure 9.14: Using custom CSS and HTML code in SurveyGizmo, we were able to create mouseover interactions of thumbnails, which showed enlarged versions of the moused-over design in the middle of the browser window. This allowed respondents to quickly compare and contrast the different designs presented on each page.

Consequently, we focused on developing a method to present multiple water usage feedback designs *within a shared visual space*. This allowed our respondents to interact with multiple designs at one time. We accomplished this via a custom CSS template that supported mouseover zoom interactions. Respondents could maneuver their mice over thumbnail-sized images of our designs on the left side of their browser window and see an enlarged version of the currently "moused-over" design in a reserved space in the middle of the window (Figure 9.14). This interaction provided a simple mechanism with which respondents could easily compare and contrast various designs without scrolling. We tested the mouseover functionality in all of the major browsers including Internet Explorer, Chrome, Opera, FireFox, and Safari on both PCs and Macs. The thumbnails were displayed with the dimensions 150x94 pixels and the enlargements 700x437.

9.2.1.2 Part 1: Isolating Design Dimensions

This survey evaluated the impact of the following design dimensions on a variety of subjective measures. The specific dimensions examined were:

1. **Data Granularity**: water usage data broken down by individual fixture, category of fixture, or activity as well as the inclusion/exclusion of hot water versus cold water usage information.
2. **Time Granularity**: by day, by week or by month or all of the above.
3. **Measurement Unit**: by gallons, by cost of water, by gallons *and* cost of water. We also explored the option of including sewage costs along with water consumption costs.
4. **Self-comparison**: with or without comparison to past usage information.
5. **Goal-comparison**: with or without comparison to a goal and along with an evaluation of preference for different types of goal-setting strategies.
6. **Social-comparison**: with or without comparison to other households along with an evaluation of different definitions of "other households."

The set of displays used for each of these dimensions is shown in the Display Designs section (as previously mentioned, the survey itself is available in Appendix E). To mitigate order effects, the design dimensions were presented in random order and the display options within each factor (*e.g.,* individual fixture, category of fixture and activity) were also presented in random order. This was done via custom scripting within SurveyGizmo.

Within each design dimension, respondents were asked to select their preferred display for helping them to conserve water and why. In addition, each of the Data Granularity designs were ranked on a 5-point Likert scale from "Strongly Disagree" to "Strongly Agree" across five subjective attributes: (i) Thought-provoking; (ii) Easy-to-understand; (iii) Attractive; (iv) Informative/Useful; and (v) Overwhelming/Confusing. These *five-point subjective measure attributes* were ordered randomly on each use. They were also used in the second part of the survey, which we describe next.

9.2.1.3 Part 2: Evaluating Design Probes

The second part of the survey evaluated three design probes: *Time-Series View, Spatial View*, and the *Per-Occupant View*. These designs were selected and refined through pilot testing. The primary goal here was to use three designs from different points in the water feedback design space to ensure that we provoked a variety of reactions with regards to issues such as privacy, competition, and household dynamics.

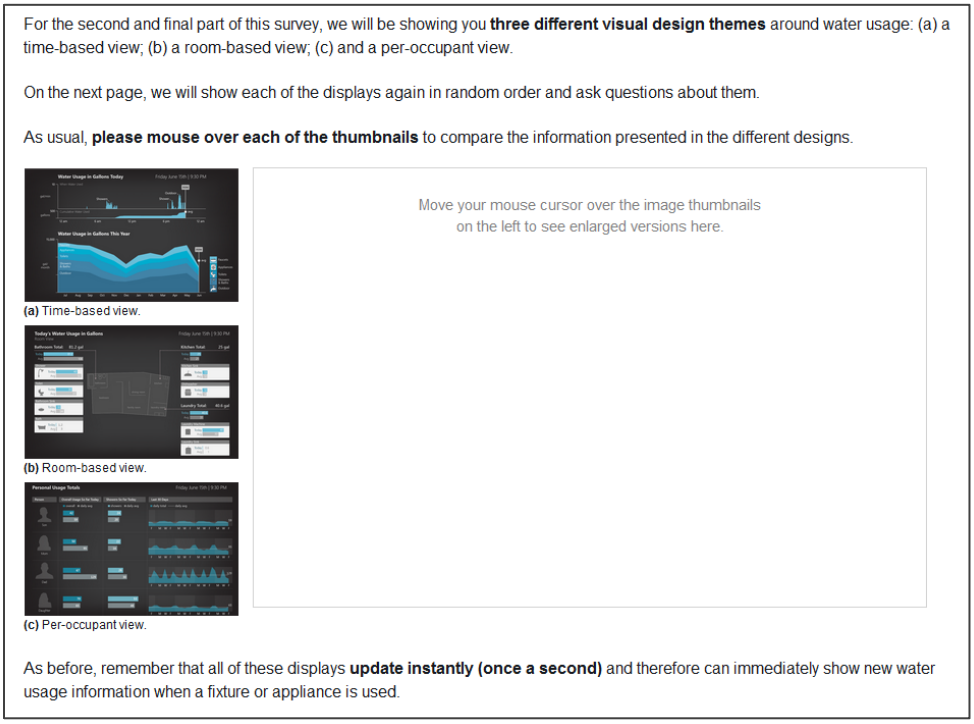


Figure 9.15: The beginning of the Design Probe evaluation part of the survey. We first presented the three design probes together on a single page to allow for comparison and then presented each design again in random order along with a standard set of questions between them.

This survey section began by presenting all three design probes on a single page to allow them to be examined together. Then, the next three pages presented the design probes in random order along with a standardized set of questions including: the five-point subjective measure attributes, asking who they thought the display would appeal to in their home and why, and how often they would look at the display. In addition, we asked two different objective questions at the beginning of each design probe page that tested the respondent's ability to correctly read the visualization (*e.g.,* which room used the most water today or what month used the least amount of water in the past year?). Note that these objective questions were included both to test the legibility/comprehensibility of the displays as well as to encourage respondents to examine the displays closely.

9.2.1.4 Pilot Testing

We pilot tested the Display Evaluation Survey to evaluate length, question wording and comprehension, and user understanding of the mouseover interaction. Seventeen participants were recruited via internal mailing lists and word-of-mouth. Our pilot testers included non-technical users and adult seniors. Similar to the Formative Water Survey, we pilot tested this survey using a staggered participation approach such that pilot testers were always seeing the most recent version of the survey. There were five iterations of the Display Evaluation Survey in all. Based on feedback from these pilot tests, we reduced and simplified the amount of text in each section and added "all of the above" options to some of the design preference questions. We also found that the mouseover interactions were not only understandable but preferred over other more static presentations of the designs.

9.2.1.5 Data Analysis

In all, there were 63 questions in Display Evaluation Survey. Although we used branching to ask some questions in random order, all questions were eventually asked for all respondents. The median survey completion time was 21 minutes. Of the 63 questions, 53 of these were mandatory and could not be skipped. The rest were optional, open-form response questions such as "why did you select this option" or asking the respondent to provide "additional comments." We were not expecting a high response rate to these optional questions nor were we expecting long, detailed feedback from those that did choose to respond. We were surprised, then, to find that of the 3,906 total optional open-form "Why?" questions, 2,608 had a non-blank response (66.8%). Of these, the average number of words provided per question was 24.4 (*Median*=20; *SD*=24). Combined with the other open-form questions, we received a total of 5,685 qualitative responses with an average word count of 21.2 (*Median*=15; *SD*=21.3; see Table 9.1). Given this large amount of qualitative data, we decided to change our coding approach from the Formative Water Survey.

In the Formative Water Survey, we had two independent coders code all open-form responses. This was not practical for the Display Evaluation Survey data. Instead, for each of the 14 open-form response questions, 50 randomly selected responses were coded by two coders following the iterative coding process described by Hruschka *et al.* (2004). A Cohen's Kappa test was used to examine inter-rater reliability; the average score was 0.75 (*SD*=0.19). The worst performing codes were "other" and "junk," which were infrequent and are not reported on below. Once the iterative coding process completed, the two coders each received an additional independent set of 50 questions for the 14 open-form questions resulting in 150 coded questions in all (50 of which were redundantly coded; these were the questions that the Cohen's Kappa test was computed over).

	Why (Optional)	Why (Required)	Additional Comments (Optional)	Totals
Num questions/survey	6	4	4	14
Total times asked	3906	2604	2604	9114
Total times answered	2608	2604	473	5685
% answered	66.8%	100.0%	18.2%	62.4%
Avg word count/answer	26.4	15.4	24.6	21.2
Med word count/answer	20	10	19	15
Stddev word count/answer	24.0	15.7	24.0	21.3

Table 9.1: A statistical breakdown of responses to open-form questions in the Display Evaluation Survey.

Note that throughout the presentation of our results, we simplify five-point Likert-scale responses to three-point to make our figures more legible. Thus, a "Strongly Disagree," "Disagree," "Neutral," "Agree," and "Strongly Agree" scale was reduced to "Disagree," "Neutral," and "Agree." Our analysis was conducted on both the five-point scales and the three-point scales and our textual discussion includes both below.

9.2.1.6 Participant Demographics

We had a total of 712 completed surveys from respondents in countries such as China, Afghanistan, Australia, Brazil, Israel, England and Spain. An additional 140 people started the survey but did not finish, resulting in a drop-out rate of 16.4% (the Formative Water Survey drop-out rate was similarly low at 18%). We were pleased with this low drop-out rate, in particular, because the Display Evaluation Survey required more time to complete than the Formative Water Survey.

In our analysis, we focus on the 651 completed surveys from the North American respondents. This was both to maintain consistency with the analysis in the Formative Water Survey as well as due to the cultural and regional differences in water usage attitudes and behaviors across the world, which may have affected the interpretation of the displays. Of the 651 North American respondents, 610 (93.7%) were from the United States and 41 (6.3%) were from Canada.

Unlike with the Formative Water Survey, we did not rely solely on URL referrer information to track how our respondents accessed our survey link. Instead, we created a number of unique URLs that all pointed to the Display Evaluation Survey and monitored traffic to each link. SurveyGizmo refers to these unique links as campaigns. We created six campaigns in all: (1) a link emailed to those who opted-in to receive a "follow-up survey" after completing the Formative Water Survey; (2) a link posted via various mailing lists; (3) a link posted to Craigslist; (4) a link posted to various social networking sites such as Twitter, Facebook and Google+; (5) a link provided at the end of the Display Evaluation Survey asking respondents to share the survey with their friends and family; and, finally, (6) a link provided at the end of the Formative Water Survey that was added when the Display Evaluation Survey was launched.

The most survey traffic came from campaign (1), the follow-up link emailed to the Formative Water Survey respondents. Of the 656 Formative Water Survey respondents in Chapter 6, 586 (89.2%) opted to be contacted about the Display Evaluation Survey. Based on our URL campaign monitoring data, 238 (40.6%) of these ended up taking the Display Evaluation Survey. Overall, campaign (1) accounted for 36.6% of the Display Evaluation Survey completions, followed by mailing lists (22.4%), and Craigslist (14.1%)—see Figure 9.16a. These statistics are estimates, however, as the links themselves can be shared outside of their initial intended audience (*e.g.,* someone could take the campaign (1) link and post it to their Facebook page).

Perhaps because we relied on a similar recruitment method to the Formative Water Survey, the two surveys had nearly identical demographics. The average age of our Display Evaluation Survey respondents was 36.1 (*SD*=13.2; *Min*=18; *Max*=94) and 59.6% were female (N=388)—in the Formative Water Survey the average age was 36.7 and 62% were female. Like the Formative Water Survey, the Display Evaluation Survey respondents were highly educated—over 80% reported four year college degrees or more. A startling 45.3% reported having a graduate degree (this was 36% for the Formative Water Survey, which is also quite high). The top five most reported professions were student (18.1%), science/technology (17.7%), education (11.7%), research (8.9%), and other (7.7%). Household income was relatively evenly spread across different income categories; however, as noted in the Formative Water Survey analysis, this is not reflective of the general US or Canadian populations (DeNavas-Walt *et al.*, 2010). Demographic breakdowns for education, profession and household income are plotted in Figure 9.17.

In terms of our respondents' attitudes and beliefs about water and the environment, we asked three 5-point Likert scale questions: (1) "I consider myself a 'green' or 'eco-friendly' person;" (2) "I am concerned about global climate change;" and (3) "I am interested in conserving water in my home." The responses are shown in Figure 9.16b. Similar to the Formative Water Survey where 88.4% of respondents reported interest in conserving water in the home, 91.4% reported interest in the Display Evaluation Survey. With regards to self-perceptions of "greenness," 75.4% considered themselves "green" and 87.1% reported concern for global climate change. As we noted in the Formative Water Survey, such a demographic is not surprising given that these surveys were opt-in and advertised as being about water usage.

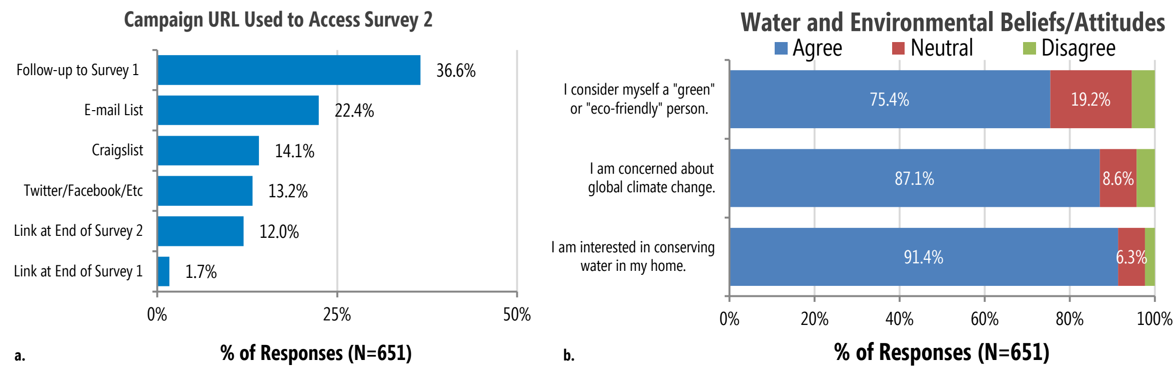


Figure 9.16: (a) A breakdown of the campaign URLs used to access the Display Evaluation Survey among completed surveys. (b) The responses to three questions about water and environmental beliefs/attitudes.

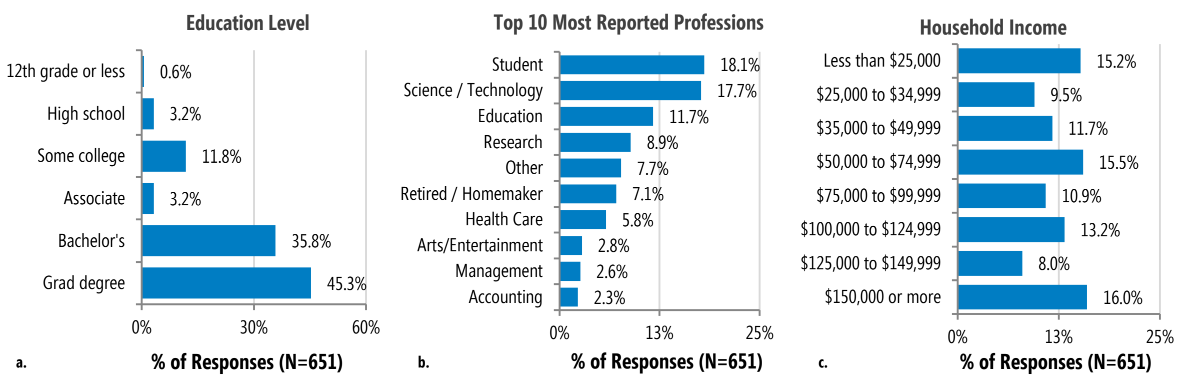


Figure 9.17: The demographic makeup of the Display Evaluation Survey respondents including (a) education level, (b) the top 10 most reported professions, and (c) household income. In summary, our respondents were highly educated and primarily in science/technology and education-related fields. The household income was more evenly divided.

9.2.2 In-Home Interview Method

In addition to the survey, we conducted semi-structured in-home interviews with 10 households (20 adults total). As with the survey, participants were recruited via email lists, word-of-mouth, and postings to websites such as Craigslist. Here, we specifically recruited *families* because we were interested in exploring differences in perspective within a household, including children's reactions to our displays. In all interviews, at least two members of the household were present for the duration of the interview. Households were compensated $65 for participating.

9.2.2.1 Interview Outline

Two researchers conducted each interview; one led the interview and the other took notes on verbal and non-verbal interactions. Interviews were audio recorded for transcription purposes. At the beginning of the interview, demographic information on the household (*e.g.,* house size and number of bathrooms) and on each participant (*e.g.,* environmental beliefs) was collected. The interview explored general water attitudes, knowledge, and practices across occupants of the home, and evaluated the eco-feedback designs. Participants were supplied with a touchscreen laptop loaded with the *data granularity* and *comparison* design dimensions as well as six design probes: *Time-Series, Geographic Comparison, Rainflow, Metaphorical Units, Aquatic Ecosystem,* and *Per-Occupant.* Due to time limitations*, Spatial* was evaluated in some, but not all interviews. The interviewer used each design to elicit both positive/negative feedback as well as to encourage discussion about how the display might be used in the home. Interviewers also focused on involving all participants during the interview so that various perspectives could be heard. During the last 10 minutes of the interview, participants were asked to select their favorite design overall and pick one or two locations in their home where they would install the display. Photos were taken of these areas with the display held in place (*e.g.,* Figure 9.18). The full interview script is available in Appendix F and the displays used in the interviews in Appendix G.

9.2.2.2 Data Analysis and Demographics

Interviews lasted 90 minutes. Adult interviewees were aged 39 on average (*Min*=18; *Max*=62), 11 were female, and 18 had four-year college degrees or more. Seven households had children (*N*=11), aged 2 to 12. In two homes, a child was present throughout the interview; typically, though, children spent 5-10 minutes with us. The average house size was 1850 sq ft with two bathrooms and 3.4 occupants. Two households rented, the rest owned. All paid for water. Table 9.2 and Table 9.3 list the household and individual interviewee demographics in more detail.

Our interview participants' occupations included a massage therapist, two attorneys, three healthcare professionals, three engineers, two teachers, and an architect (among others). Similar to our survey, most participants were environmentally conscious: 90% indicated interest in conserving water in their home, all were concerned about global climate change and 85% considered themselves "green" or "eco-friendly." Despite this interest, many had misconceptions about water usage amounts in their homes. For example, the mother in household three overestimated that her average morning shower used 400 gallons of water and many identified their dishwasher as their top water user (dishwashers account for 1% of water use in the average US home: Vickers, 2001). Interview data was coded and categorized into overarching themes.

Household ID	Interview Length (mins)	App. Sqft Residence	# of Bedrooms	# of Bathrooms	# of Adults	Total Occupants	House/ Apartment	Own/Rent	Pay for water?
1	86.4	1200	2	1	2	2	House	Rent	Yes
2	57.8	1850	3	2.5	2	4	House	Own	Yes
3	103.8	2800	3	1.75	1	2	House	Rent	Yes
4	87.3	989	2	2.5	2	2	Condo	Own	Yes
5	84.9	1850	3	1	3	4	House	Own	Yes
6	80.3	1400	3	1.25	2	3	House	Own	Yes
7	92.2	2500	4	2	2	4	House	Own	Yes
8	104.3	2500	5	2.5	4	7	House	Own	Yes
9	83.9	1900	3	2.5	3	3	House	Own	Yes
10	77.9	1500	3	2	2	3	House	Own	Yes

Table 9.2: Household demographics from in-home interviews. H8 has high occupant count because of tenants.

Household ID	Individual ID	Age	Gender	Profession	I am interested in conserving water in my home.	I consider myself a "green" or "eco-friendly" person.
1	1.1	31	Female	Science/Technology/Programming	Strongly Agree	Strongly Agree
1	1.2	33	Male	Research	Strongly Agree	Strongly Agree
2	2.1	35	Female	Education, Research	Strongly Agree	Agree
2	2.2	38	Female	Social service	Agree	Neutral
3	3.2	56	Female	Health Care, Other: Massage Therapist	Strongly Disagree	Strongly Agree
4	4.1	28	Female	Administration/Clerical/Reception	Strongly Agree	Strongly Agree
4	4.2	26	Male	Other: Communications	Strongly Agree	Agree
5	5.1	32	Female	Education	Strongly Agree	Strongly Agree
5	5.2	32	Male	Science/Technology/Programming	Strongly Agree	Strongly Agree
6	6.1	41	Female	Consulting	Agree	Agree
6	6.2	41	Male	Architecture/Design	Strongly Agree	Neutral
7	7.1	41	Female	Accounting/Finance/Banking	Strongly Agree	Agree
7	7.2	44	Male	Science/Technology/Programming	Strongly Agree	Agree
8	8.1	44	Male	Attorney	Agree	Agree
8	8.2	47	Female	Other: Public Policy and Law	Strongly Agree	Strongly Agree
9	9.1	52	Female	Health Care (Physical & Mental)	Strongly Agree	Strongly Agree
9	9.2	62	Male	Health Care (Physical & Mental)	Strongly Agree	Agree
10	10.1	40	Male	Education	Strongly Disagree	Agree
10	10.2	37	Female	Attorney	Strongly Agree	Strongly Agree

Table 9.3: A subset of the individual demographics that we collected on our interview participants. Note that we instructed our participants that we would *not* look at their questionnaire responses until after we returned to our research lab.

9.3 FINDINGS

We now present findings from the online survey and the in-home interviews. We use respondent (*R*) and interviewee (*I*) to refer directly to a survey or interview participant. The word “participant” refers to both. We take care to explicitly specify the source when relevant. For the surveys, we captured both quantitative and qualitative data. The interviews, largely qualitative in nature, were meant to both contextualize our survey findings as well as to capture and probe more nuanced feelings about our designs. In addition, as the interviews took place in the interviewees own homes, we could better explore reactions to how the displays fit into domestic space. Note that percentages appearing in the text are from the survey only, unless otherwise noted.

Data Granularity	N%	Comparison	N%
Individual fixture	53.6%	**Self-Comparison**	**91.0%**
Fixture category	27.0%	**Goal-Comparison**	**68.2%**
Activity	19.4%	Set manually	58.1%
Hot/Cold Breakdown		Set by display	44.1%
Hot/Cold always	47.5%	Set to efficient neighbors	37.4%
Switch between both	43.8%	Set by supplier	21.8%
No hot/cold info	8.8%	Set by local government	16.9%
Time Granularity		**Social-Comparison**	**67.7%**
Switch between all 3	64.5%	Demographically similar	73.0%
By week only	15.5%	Geographic neighbors	52.4%
By month only	10.1%	Households in other cities	35.6%
By day only	9.8%	Households in other countries	32.4%
Measurement Unit		Select Family/Friends	35.2%
Display both together	71.4%	Comfortable sharing data anonymously to enable social comparisons	78.8%
Gallons only	16.0%		
Cost only	12.6%		

Table 9.4: Survey responses (*N*=651) to our design dimension questions. The responses for each dimension in the left column were exclusive options; thus percentages add to 100. The comparisons (right column) were individual 5-point agreement Likert scales (% here represents number of respondents who selected "Strongly Agree" or "Agree").

9.3.1 Isolating Design Dimensions Findings

As the interviews primarily focused on the design probes, a majority of findings reported in this section are from the online survey with supplementary data from the interviews. Table 9.4 shows the preference breakdown for each dimension evaluated in the online survey.

9.3.1.1 Data Granularity

When asked about which data grouping display would be most useful in helping to conserve water, a slight majority of respondents (54%) preferred the individual fixture view (versus fixture category and activity). Most of these respondents mentioned advantages in the specificity of data that view provided, including the ability to target reduction efforts at certain fixtures and the ability to identify maintenance issues such as leaks. R536 provided a representative response incorporating these advantages:

> *"It [the individual fixture view] would be easiest to tell if a certain fixture is leaking or inefficient, or if certain members of the household are using more water, etc. This display lets you more easily identify the specific areas that need attention" –R536*

The fixture category view was the second most preferred design, receiving 27% of the votes, most often because of its balance of information: "…just enough information to help me understand exactly where I'm using water without being overwhelmed" (R767). Many respondents also mentioned being able to switch to the individual fixture view when necessary: "I would like that to be a secondary screen to hone in on data" (R363). Finally, 19% of respondents preferred the activity view. Overwhelmingly, these respondents expressed that this portrayal was the most actionable and intuitive because it emphasized *behaviors* rather than *fixtures*. For example, R48 mentioned:

> *"[The activity view] makes it so much easier to visualize what actions I need to take in order to reduce water usage (e.g., 'turn the tap off while shaving' vs. 'be careful running the tap in the second upstairs bathroom')." –R48*

We found similar preferences in our interviews, though no one preferred the activity view because it seemed more difficult to determine *where* water use occurred.

IMPLICATION: Although there is a general preference toward specific information at highly granular levels (*e.g.,* at the individual fixture level), this data should be supplemented, when possible, with recommendations about what *actions* can be taken to reduce usage.

9.3.1.2 Hot/Cold Breakdown

Nearly *all* respondents wanted to see a hot/cold breakdown of water usage (91%), either on its own (48%) or with the ability to switch between the breakdown and overall usage (44%). For respondents who wanted hot/cold information, the relationship between hot water use and energy consumption was a commonly cited theme:

> *"Hot water uses so much energy to produce and I think that it is interesting to see how much of each is being used… it might encourage people to use less hot water." –R668*

For the small portion of respondents that did not want hot/cold information (9%), popular responses included perceiving hot water use as a necessity or that water temperature was unrelated to water conservation.

IMPLICATION: This is an important new finding; no past work has distinguished between hot and cold water usage amounts in their displays. Future systems should integrate this information.

9.3.1.3 Time Granularity

The majority of participants (65%) felt that being able to *switch* between days, weeks and months would be the most useful in helping them to conserve water. In general, these respondents recognized that there were advantages and disadvantages of each view in terms of the information afforded. For respondents who felt that the day view would be the most useful (10%), a commonly cited reason was the immediacy between individual actions and the feedback. Respondents who preferred the week view (16%) cited that it offered a balance between the immediacy of daily information and the stability of monthly information. Finally, for respondents who preferred the month view (10%), two common reasons were that it paralleled their billing cycle and that they predicted that they would *not* be interested in looking at the display more frequently. For all time granularities, there was recognition that the time window selected would emphasize/deemphasize underlying temporal routines or patterns in the home and that this would influence when and how the information would be used. For example, R664 notes "We live our lives in cycles of weeks... seems like this view would most closely match other patterns in our lives" (ellipses from original quote).

IMPLICATION: Different time windows are amenable to different actions and interest levels. Designers should make it easy for users to explore different temporal ranges, these "drill-down" actions will be infrequent, meaning that a reasonable default (*e.g.,* week view) should be set.

9.3.1.4 Measurement Units

Similar to the above, most participants (71%) preferred to be able to switch between gallons and dollars, recognizing the usefulness of both metrics. R143 summed this perspective up well:

> *"Seeing the gallon amount triggers the 'save the environment' impulse to conserve, while the dollar amount is helpful because almost everyone is motivated by money to some extent." – R143*

Respondents who preferred to see *only* cost (13%) commonly cited the understandability of dollars compared to gallons, CCFs or liters, and/or felt that money was a strong motivator. For example:

> *"I don't think very well in 'thousands of gallons', but $20 I can understand. That's a case of beer down the drain, if you will." –R48*

In the interviews specifically, some interviewees observed how displaying cost information broken down by fixture would allow them to rethink the cost of water: "[it] puts a price on your activity. I've spent $14 on showers this month" (I1.1). Also in the interviews, we examined the use of visual metaphors such as gallon jugs to make water use seem more tangible (*e.g.,* Figure 9.12). Although most interviewees responded positively to these representations and some found them "shocking" (I4.2), they did not think they were necessary to see all of the time.

For those participants who did *not* want dollars as a measurement unit, many cited the low price of water as making cost irrelevant while others simply stated that conservation for ethical reasons was their main motivation. Interestingly, some respondents mentioned the potential negative effect of water's low cost on conservation, for example: "Water is cheap in some places, so I think seeing a low number for cost could be an anti-motivator" (R93).

We also asked about the inclusion of sewage cost information: most respondents (61%) wanted the cost of sewage in the display with reasons including a more accurate depiction of the water bill cost and the belief that higher cost be an additional incentive to conserve. Others thought that cost, no matter what, was not a motivating factor or incorrectly thought that sewage was not relevant to water conservation. "Who cares? Doesn't have anything to do with consumption" (R197) and "the link between water conservation and sewage use is not clear" (R284).

IMPLICATION: Water feedback displays should include both volumetric units and cost. However, water is cheap, especially when compared to energy, and may serve to discourage conservation for some people. Adding the cost of sewage and hot water heating may mitigate this issue.

9.3.1.5 Comparison

Comparisons were the most uniformly desired pieces of information of all the dimensions. In the survey, an overwhelming majority were interested in comparing their household's current usage to the past (91%), followed by comparing to a goal (68%) and to others (68%)—see Table 9.4. A similar preference was found in the interviews; however, here, more people were interested in social-comparison than goals, with some noting that they would never set goals. For those participants interested in self-comparison, popular reasons included that it contextualized or provided perspective on current usage, would motivate them to conserve (*e.g.,* by "beating" their past performance), and/or would help identify where to target conservation effort, by showing typical use; for example, "[the comparison] helps me put the numbers in context so they mean something to me" (R2).

Although a majority of participants were interested in comparing their usage to a goal, feelings were mixed about how this goal should be set. Most preferred having the goal *manually* set by members of the household compared to automatically by the display system or by the local government or water supplier (Table 9.4). Interviewees were more amenable to externally set goals if they were provided with a justifiable reason (*e.g.,* low reservoir levels).

In terms of social comparison, a majority of respondents agreed (68%) that they would want to compare their water usage with other households and 79% indicated that they would feel comfortable sharing anonymous fixture-level usage data to enable these comparisons. The most popular social-comparison target in both the survey and interviews was demographically similar households (*i.e.,* houses with similar size and number of occupants). Interestingly, comparing to geographic neighbors was less popular (52%). Most interviewees questioned the fairness of this comparison: "the thing is, you just don't know if you are comparing apples to apples" (I9.2).

IMPLICATION: Some form of self-comparison is important. Although social-comparisons are of interest and people are willing to share their fixture-level data to enable them, eco-feedback systems should offer a rationale for any external comparison targets. User control and system transparency are also important aspects for goal-setting.

9.3.1.6 Summary of Findings

Overall, there was a strong preference for specific, detailed information about water usage at the *individual fixture level* in both volume and cost metrics. Our participants also strongly preferred the ability to see their usage broken down by hot/cold and their usage contextualized by some sort of comparison data (self-comparison was most preferred). This level of specificity further motivates the need of the emerging, highly-granular water sensing systems (*e.g.,* HydroSense, Chapters 7 and 8). In general, our participants also recognized the need for interactivity and wanted the option to view data with different time windows and measurement units; however, defaults should probably be the *week* view with both cost and volumetric information.

9.3.2 Design Probe Findings

In comparison to the design dimension displays, the design probes elicited a much greater range of responses. We first summarize reactions to these displays, and then focus on synthesizing higher-level emergent themes such as competition, accountability, and playfulness.

9.3.2.1 Specific Preferences

At the end of the survey and interviews, we asked participants to select their favorite design(s). In the survey, respondents could choose between a bar graph view or one of the three design probes: *Time-Series, Spatial or Per-Occupant*. The majority preferred the bar graph (64%) because it was simplest and most glanceable. Among those respondents who preferred a different design, the votes were nearly an even split: 14% for *Spatial*, 12% for *Time-Series*, and 10% for *Per-Occupant*. In the interviews, each interviewee was asked to select their top three designs including the bar graph view and *all* of the design probes. The comparison based displays were selected most commonly (12 times), followed by the *Individual Fixture Bar Graph* view (10), the *Time-Series* view (9), the *Aquatic*

Ecosystem (8) and the *Fixture Category Bar Graph* (7). Unsurprisingly, in 8 of the 10 homes, there was not perfect agreement among interviewees on which were the best displays. This suggests that multiple feedback options should be made available.

For the *Time-Series* view, which was arguably the most complex, participants liked being able to see longer-term temporal patterns and the effect of reduction efforts in the graph. In contrast, the main reason stated for preferring the *Spatial* view was that the floorplan made information easier to read and understand: "The breakdown between rooms and appliances is clear and gives an intuitive sense of where water is being used" (R182). For those that selected the *Per-Occupant* view, primary reasons included notions of accountability (*i.e.,* pinpointing *who* was using water) and competition. Finally, for *Aquatic Ecosystem*, interviewees were attracted to the idea of "turning consumption on its head and rewarding saving" (I1.2), because it was good for children, and/or because it more was ambient, "like a screensaver" (I5.2). In the next section, we further explore these reactions in the context of higher level themes.

9.3.2.2 Emergent Themes

Competition and Cooperation

Competition was a polarizing theme that arose, most often with the *Per-Occupant* and *Aquatic Ecosystem* designs. Those who liked it pointed to motivating properties of competition, notions of gaming and beating past low usage scores, and creating "friendly competition" with others (R220). Those who disliked it felt household water savings was about *cooperation* rather than competition. They felt the *Per-Occupant* display "pits the family members against each other rather than encouraging collaboration." (R485). Some worried how this display went against the non-competitive ethic that they were trying to create in their home: "[it] sets up a 'competitive' environment that we are trying not to create in our household" (R493). In contrast, the *Aquatic Ecosystem* seemed to better support cooperation; for example, I1.1 thought that it was a "clever way of turning water usage into a game," "kid-friendly," and "a good way of working towards goals together."

IMPLICATION: Though competition was recognized as having motivating properties, some found it disconcerting and potentially inhibiting towards the goal of saving water. One simple solution here would be to make those elements or displays that specifically encode competition optional. Another is to make the comparative elements stress collaboration rather than competition (*e.g.,* by making the focus of comparison other households).

Accountability and Blame

As with competition above, the ability to observe *who* used water was polarizing. This was the case with *Spatial* view, and, most particularly, the *Per-Occupant* view. Some liked the ability to pinpoint *who* was using water (*e.g.,* these designs made it easier to know who may need to reduce their water usage): "it holds each individual accountable for water usage" (R354). Some even offered pragmatic suggestions about how this data could be used: *e.g.,* for bill splitting. However, there was a distinction between those who felt that this data could be used to hold people accountable for their behaviors and those that felt that this would lead to blame and household conflict. This was particularly true for *Per-Occupant*:

> *"I don't think there's any reason to add an element of 'blame' to conservation efforts within a family. If I received information in this format, I would throw it away without looking at it" –R98*

> *"Would seem to lead to plenty of arguments about usage" –R144*

Participants also recognized that such inferences could be made with other designs (*e.g.,* by observing who uses the master bathroom shower).

IMPLICATION: There is a thin line between enabling accountability and introducing elements that could be perceived as blame inducing. As with competition, there is clearly a contingent of people attracted to the idea of knowing *who* uses water. However, any eco-feedback system that tries to encode accountability explicitly should make this part of the system optional.

Simplicity and Glanceability

Although we knew that some of our design probes were more sophisticated and visually complicated than the bar graph views, we did not expect such universal gravitation towards *simplicity*. This trend, perhaps, could be attributed to our evaluation methodology—given that we did not conduct field study deployments, the reactions we measured were based on first impressions and not on actual use experience. However, when a visualization was not immediately understood, it was often met with skepticism at best and disgust at worst. This will directly contribute to adoption and use of the display. For example, "I wouldn't even spend the time [to figure it out]. I don't even want to take the time to look at it" (I9.2).

Playfulness and Functionality

The more playfully oriented designs were evaluated in the interviews only. The *Aquatic Ecosystem* and *Rainflow* elicited responses about playfulness and utility. Most interviewees reacted positively to the aesthetics and ideas of these two designs, particularly the *Aquatic Ecosystem*: “it’s clever, I love it” (I1.2) and “I like the idea of getting rewards for saving water” (I8.1). While 12 interviewees chose one of these designs in their top three, only 2 out of 20 chose one as their *most* preferred. The tension between utility and playfulness is embodied here:

> *“It’s like unlocking badges in Foursquare. No matter how trivial it can be to make a fish appear on this screen, you still want to do it” –I4.1*
>
> *“It doesn’t appeal to me as much. I don’t do Foursquare. This distracts me a little bit and it doesn’t make me think about my usage.” –I4.2*

Similarly, for *Rainflow*, although many thought that it was “interesting”, “fun” and “pretty”, participants weren’t sure that it was *functionally* better than a normal bar graph: “it looks cooler, but I’m not sure it’s more useful than the bar graphs” (I8.1).

For those households with children, many felt that these displays could be useful as an educational tool as well as to get their children involved in the concept of conservation at home. However, some worried that their children might become overly involved in trying to earn rewards by not cleaning themselves or flushing. Others were also concerned about how their children would react if a fish died or what would happen if they reached a minimal level of usage in their home. For *Rainflow,* some parents mentioned how it might actually encourage their children to use water just to see the pretty water flows.

IMPLICATION: Playful and fun designs can be good at creating engagement and interest but the *actionability* of the data is what is paramount for most. In addition, designs that are more ambient need to take care not to look more visually interesting with increased consumption.

Privacy

Disaggregated water usage feedback can reveal information about otherwise latent patterns and routines about a household (*e.g., where* and *when* people are in the home). Such revelations can be obscured by simple changes to the interface: *e.g.,* a bar graph view of a day makes it more difficult to assess *when* an occupant woke up, went to work, and went to bed, compared to a timeline view. Although some notions of privacy arose from our *Time-Series* and *Spatial* displays with references to "big brother" (R826), "creepy" (R5), and being able to see when people were "regular" (I9.1), privacy was a major reason why some participants reacted negatively to the *Per-Occupant* display. Because this design emphasizes *who* is using water rather than *what*, it provoked the most comments about surveillance, intrusiveness and violations of boundaries:

> *"It's incredibly invasive. And other people's water consumption is not my business." –R25*

> *"water usage for many purposes can be very personal, and shouldn't be automatically shared." –R246*

Interestingly, some respondents recognized that similar information could be derived from other designs but that these did not feel as surveillance-oriented:

> *"This display comes across more 'big brotherish' to me to assign usage to specific people and I didn't feel that way when being assigned to appliances/faucets even though those can often be tied back to specific people" –R84*

In contrast with the survey results, most of the interview participants, when asked, had not even thought about the privacy implications of the designs. Even after providing specific scenarios about how people could be tracked (*e.g.,* "see, here you could tell that your son skipped school because of his bathroom usage during the day"), privacy was not considered a significant issue.

> *"Maybe if my daughter was a teenager, she wouldn't want me to track her but I'm not that kind of Mom" –I3.2*

> *"We are more tightknit than the average family because of our house size and everything… we tend to know a lot about each other (laughter)". –I1.2*

IMPLICATION: Privacy is an important aspect of future eco-feedback displays in the home, particularly as sensing systems become more granular. Designers need to take care to offer different levels of abstraction to make particular events in the home less visible in some views.

9.3.2.3 Display Placement

At the end of the interview, we asked participants to select one or two places in their home where they would install the water feedback display. The first choice was the kitchen (6), followed by a highly trafficked area of the home such as a hallway (5), near the thermostat (5), or in the shared upstairs bathroom (1). Reasons for these placements included being in an accessible location for all occupants to see and being able to see information multiple times a day at a glance (*e.g.,* when

Figure 9.18: Preferred display locations in (a) H5, (b) H4, (c) H1, (d) H10, (e) H6, and (f) H8. Most selected a highly visible, easily glanceable location (*e.g.*, H5 and H4 selected the kitchen and H1 and H10 selected hallways). H6 and H8, however, preferred behind the cupboard or in a closet next to the gas meter.

cooking). Interestingly, two households selected locations that were *inaccessible* on purpose: H6 wanted the display mounted inside their kitchen cupboard (Figure 9.18f) and H8 wanted it in their storage closet next to their gas meter (Figure 9.18e). The reason given for these placements was that they did not want technology infiltrating all aspects of their life, for example:

> *"We would just pull it up [the water usage data] on our computer and would use the display occasionally if we had time and were curious." (I8.2, Female, 47)*

When selecting a location, most homes took into account *who* could see the display—either other householders or guests: "[if we placed it here], the kids couldn't see it" (I2.1). Some participants mentioned how guests may be able to see the data, which was perceived either positively or negatively. I7.2, for example, thought that the *Aquatic Ecosystem* could be used to "brag to our friends when they come by." However, H9 took the opposite view:

> *"If we hang it here [Bob] and [Jane] would come over and they would look at it. I'm not sure I like that." –I9.1*

> *"Yah, if you just had Nemo floating around then you could put it here, but otherwise I wouldn't necessarily want people to see it." –I9.2*

IMPLICATION: There was a preference towards placing displays in shared and highly trafficked areas of the home, yet a privacy tension exists since these are also the more "public" areas, viewable by guests. Future work should explore display form and placement more deeply, particularly since only bathroom feedback displays have been previously studied.

9.3.3 Summary of Findings

The design probes elicited strong and sometimes polarizing reactions. Although some designs provoked positive feelings of competition, accountability, and playfulness in some people; in other people, these same designs felt intrusive, blame-inducing, or antithetical to the goal of saving water. The key here is to realize that eco-feedback displays do not just visualize consumption, they document *household activities*. Consequently, designers have to take into account how their displays may affect underlying social dynamics in a household and expose otherwise latent routines. Our findings suggest that these issues could affect whether a display will be accepted into the home.

9.4 LIMITATIONS

One limitation of this research is that the study populations in both the survey and the interviews were skewed towards an environmentally interested demographic. While this sample may arguably be representative of early adopters of eco-feedback systems, studying reactions to the displays with a broader range of people, particularly, those who do *not* consider themselves eco-friendly, is an important area of future work. The study findings are also based on insights from the initial reactions of our designs rather than from real, long-term use. This may have placed an overemphasis on initial impressions: for example, many participants stated interest in having a data rich, detail oriented display; however, in a day-to-day usage, participants may prefer a more ambient display. Future work is needed to address this point.

With that said, the methods used in this chapter allowed us to explore promising design dimension and themes, which we argue is particularly important given the lack of past work studying disaggregated resource consumption data. We also used the in-home interviews to complement the survey data, since the interviews more directly allowed families to consider how a physical eco-feedback display would fit into their home. These methods follow from the participatory design process common in HCI and this chapter serves as an example about the ways in which we feel HCI/Ubicomp research fits into the eco-feedback design and evaluation process. Future work will need to take the findings provided here and apply them in functioning, interactive systems, and, ultimately, field deployments.

9.5 CHAPTER SUMMARY

As the first work in the area of visualizing *disaggregated* water resource consumption data, this chapter explored a broad range of novel eco-feedback designs to examine and uncover particularly promising elements as well as to investigate how such granularity of data may affect household dynamics. Through the use of a basic bar graph design, we first examined and uncovered design dimensions perceived as particularly useful. We found widespread interest in displaying data at the *individual fixture level* with hot and cold information and comparisons used to contextualize performance. We then evaluated six design probes that integrated multiple dimensions and allowed us to examine more complex issues such as competition, motivation, and privacy. Our findings are relevant not only to HCI researchers interested in building future eco-feedback systems but also to utilities, billing services, and professional designers working in eco-feedback for electricity, gas, and water.

Chapter 10
Conclusions and Future Work

At a high level, the goal of this dissertation has been to design, develop, and evaluate sensing and feedback technologies to promote proenvironmental behavior and decision making. Our approach was fourfold: (1) to draw upon behavioral science, environmental psychology, information visualization and past Sustainable HCI research to create a series of guidelines and dimensions to help both the *design* and *evaluation* of eco-feedback systems; (2) to study environmentally impactful human behaviors around transit and water usage to help uncover insights into how eco-feedback may play a role in increasing awareness and informing behaviors; (3) to create and evaluate new types of *sensing* systems to enable eco-feedback systems that were previously not possible; (4) and to design, develop and evaluate *novel eco-feedback* interfaces and systems themselves. Below, we first summarize the contributions of this dissertation before highlighting limitations and areas for future work.

10.1 CONTRIBUTIONS

In this section, we restate the contributions listed in the Introduction chapter and summarize how each of these contributions was achieved. Recall that the contributions are organized around three high-level areas: *foundational* contributions, *sensing* contributions, and *feedback* contributions.

10.1.1 Foundational Contributions

Our foundational contributions: (1) demonstrated and articulated the role of HCI/Ubicomp research in the design and evaluation of eco-feedback technologies; (2) uncovered attitudes, knowledge, behaviors, and perspectives around personal transportation and water usage in the home. These contributions should be useful not only to shape the design of eco-feedback systems but also to guide general eco-feedback research agendas in HCI/Ubicomp.

1. Assessing the role of HCI in the design and evaluation of eco-feedback systems. HCI/Ubicomp's recent entry into the design and evaluation of eco-feedback systems compelled us to ask: what roles should HCI/Ubicomp play in this interdisciplinary research space and how can HCI/Ubicomp best leverage methods, approaches, and findings from other, more established fields in the design and evaluation of eco-feedback technology? We addressed these questions in Chapters 2, 3 and 4 by examining and comparing design approaches, artifacts, and evaluation methods of eco-feedback technology in HCI/Ubicomp compared with other disciplines.

Our findings show that, although the environmental psychology community invests much effort in conducting longitudinal behavioral studies on the impact of eco-feedback, the *design* of the eco-feedback interface itself is rarely evaluated. Fortunately, the visual design, form, and usability of the eco-feedback system and how these factors may impact behavior are core areas of HCI/Ubicomp research. In addition, whereas environmental psychologists typically evaluate existing, commercial off-the-shelf eco-feedback systems, HCI/Ubicomp researchers are not limited by current sensing and visualization techniques. Instead, as demonstrated by many of the examples in Chapters 2, 3 and 4, HCI/Ubicomp research has been active in generating new types of sensing systems, novel visualization strategies, and new types of interfaces and interactions for eco-feedback systems. In this way, HCI/Ubicomp can help push the field forward by pursuing more exploratory paths than would otherwise be taken. For the more promising novel systems, future research will need to move beyond short laboratory and field studies into longitudinal deployments that can assess how the eco-feedback systems will be adopted and, potentially, impact behavior.

Finally, as an emerging area, the design processes and study methods used to design and evaluate eco-feedback systems are changing; however, the key takeaway here is that all disciplines working in this area (including HCI) should better integrate eco-feedback research findings from other fields. It is my hope that, in the future, HCI/Ubicomp researchers will initiate collaborations and work more closely with environmental psychologists (and other related disciplines) such that differences in expertise can be leveraged and, ultimately, eco-feedback designs and evaluations can be improved.

2. Formative studies of personal transportation attitudes, behaviors and routines to inform the design of eco-feedback systems for transit. In Chapter 5, we performed two formative studies of personal transportation practices. The first study, an online survey of 63 respondents, showed that few people considered the environmental consequences of a transportation decisions and less than half felt they were doing everything they could to travel in an eco-friendly manner. The second study, a one-week experience sampling (*in situ*) field investigation with seven participants, showed that people considered practical barriers (*e.g.,* time-to-destination) and additional motivations (*e.g.,* exercise gained from bicycling) in making their transit decisions. These findings suggest that demonstrating the benefits of eco-friendly travel in terms of additional factors such as efficiency, cost and exercise may be useful in motivating green travel. However, a major challenge for eco-feedback transit tools is in overcoming barriers to green transit, some of which actually do exist and others of which may only be *perceived* (*e.g.,* taking the train may actually be faster than driving during commuting hours). Findings from both studies were useful in guiding the design of UbiGreen, our mobile phone-based eco-feedback system for personal transit (contributions 4 and 7 below).

3. Formative studies of residential water usage attitudes, behaviors and routines to inform the design of eco-feedback systems for water. In Chapter 6, we examined residential water usage through an online survey of 656 North American respondents. The goal was to uncover limits in knowledge as well as conceptions/misconceptions about water usage in the home with the intent of informing eco-feedback designs. The findings motivate the need for better water feedback systems in the home. *One third* of respondents received no monitoring or feedback about their consumption whatsoever. Respondents also had an inaccurate conception of what fixtures and appliances typically use the most water (*e.g.,* reporting the dishwater to be a high water user when in fact it is typically very low). Finally, respondents grossly *underestimated* the amount of water required for common activities such as showering and lawn watering. These "water literacy" findings are particularly surprising given that the vast majority of our respondents had proenvironmental leanings and were, admittedly, interested in water conservation. Misconceptions about water are likely to be even more prevalent in a general population.

The findings from Chapter 6 also have implications for water-based eco-feedback displays. For example, measures such as gallons or liters were better understood than flow rates (*e.g.,* gallons-per-minute). In addition, *comparison*, a well-known and effective motivation technique seems underutilized in the water industry; only 27% of respondents had some sort of comparison on their water bills. Respondents were also generally more interested in self-comparisons than social-comparisons. Finally, we also reviewed literature from the water management community to uncover factors that influence water consumption, how water is different from other resources in the home, and primary motivators for water conservation. To our knowledge, these factors, such as the low price of water have not been previously integrated into the design of water-based eco-feedback systems. Combined, these formative studies and literature review can inform the design of eco-feedback systems for water usage and point to the potential of such systems for increasing consumption knowledge and water literacy.

10.1.2 Sensing Contributions

The primary sensing contribution in this dissertation is HydroSense: a system that significantly advances the state-of-the-art in water sensing by disaggregating water usage from a single installation point. A secondary sensing contribution is our novel sensing system for semi-automatically tracking personal transportation routines in UbiGreen. Both systems provide unprecedented levels of sensing granularity and point to the potential of fine-grained granular sensing and activity inference to enable new types of eco-feedback interfaces and visualizations.

4. A method for tracking transit behaviors using automated sensing and self-report. Our goal was to build an eco-feedback system that would sense and feedback information about everyday transit usage. Thus, we needed a sensing method capable of sensing a broad range of transit activities from car usage to walking to taking the bus. Although previous research has examined using wearable sensors, cell tower infrastructure, or self-report to track human transit patterns, our research is the first to combine these three methods into a single working system.

5. Design and evaluation of a sensor for automatically determining fixture-level water usage events from a single, low-cost sensor. We introduced a novel sensing system called HydroSense (Chapters 7 and 8), which provides three main contributions: (i) a method for identifying and classifying water use through a pressure sensor installed in an arbitrary location on the home plumbing system; (ii) a method for calculating real-time flow estimates for disaggregated events (*i.e.,* at individual fixtures) and (iii) a method for disaggregating overlapping or compound water events. Given sufficient calibration, HydroSense can also discriminate between hot and cold water usage. HydroSense represents the next phase in home resource consumption sensing with a focus on *disaggregated* usage data rather than *aggregate* usage, as has been the norm for a century or more. Easy-to-install sensing technologies such as HydroSense offer several benefits for eco-feedback systems since the homeowner maintains control of the data and can install/modify the sensing system at will.

To validate HydroSense, we performed two evaluations: (1) a controlled experiment of staged water usage events in 10 homes (Chapter 7); and (2) a longitudinal five-week evaluation of real-world water usage in five homes (Chapter 8). In the controlled experiment, we showed that a template-based classification approach classified *individual fixtures* with 97.9% aggregate accuracy. We also showed that an appropriately located and calibrated system could estimate water usage amounts with error rates comparable to empirical studies of traditional utility-supplied water meters (~10%). For the real-world water usage data collected in the second evaluation, our initial inference algorithm was no longer sufficient. As such, we moved from a strict template-matching approach to a novel Bayesian approach that incorporates template matching, a language model, grammar, and prior probabilities. We showed that with a single pressure sensor, the Bayesian approach could classify pre-segmented real-world water usage at the fixture level with 90% accuracy and at the fixture-category level with 96% accuracy. With two pressure sensors, these accuracies increased to 94% and 98%, respectively.

The algorithm adaptations required for the second HydroSense evaluation highlight a secondary contribution of this work: demonstrating the importance of field evaluations for novel sensing systems. Too often in Ubicomp research, sensing techniques are only evaluated under controlled conditions (such as we did in Chapter 7). Although these evaluations are useful in demonstrating the feasibility of a sensing method, accuracy rates can be artificially high and, in some cases, the algorithmic approach can be flawed because the controlled data is much easier to work with than real usage data. Thus, after assessing the feasibility of a sensing method, it is crucial that field deployments are conducted to provide ecological validity.

10.1.3 Feedback Contributions

For our feedback contributions, we designed, developed, and evaluated feedback systems for transit and water. Our goal was not to evaluate how these systems could change behavior specifically (a longitudinal behavioral intervention would be required here) but rather to lay the groundwork for such studies by uncovering factors that would limit the effectiveness of the feedback or challenge its adoption. In addition, through our feedback studies and those of other researchers, we synthesized design approaches and possibilities in an eco-feedback design space that provides both a critical lens with which to analyze existing designs as well as a guide to help build and evaluate new ones.

As eco-feedback is an emerging research area, our studies offer new strategies for eco-feedback evaluation that, to our knowledge, have not been previously conducted. For example, the use of a design space to direct and guide eco-feedback explorations, the use of online surveying to evaluate design dimensions, and in-home interviews with a prototype system to begin to tease out how eco-feedback designs may fit into domestic space. Our own findings in Chapters 5 and 9 and the design space in Chapter 4 should be applicable beyond transit and water eco-feedback but to all eco-feedback systems in general (including bills and online websites).

6. An eco-feedback design space to guide the development and evaluation of eco-feedback systems. In the last decade, eco-feedback has become an active and burgeoning research area and commercial enterprise. Eco-feedback systems have taken many forms including: point-of-consumption displays, information dashboards, mobile tools, ambient indicators, artistic visualizations, analytical interfaces, and feedback embedded in smart appliances. The design of these eco-feedback systems often requires a range of expertise spanning technical and non-technical domains such as computer science, electrical engineering, environmental psychology and information visualization. As such, designing and evaluating eco-feedback is an enormous challenge. And yet, there have been few attempts at providing a theoretical foundation and a comprehensive framework to guide the design process.

Based on a comprehensive literature review of eco-feedback technologies (parts of Chapters 2, 3 and 4) and our own experiences designing and evaluating eco-feedback systems, we provided an eco-feedback design space in Chapter 4, which serves four high level goals: first, by offering a tangible structure with which to think about and understand various design elements, the eco-feedback design space helps designers approach the eco-feedback design process and think concretely about various tradeoffs. Second, the design space materializes otherwise implicit assumptions about how feedback could be and should be structured. Third, it introduces a common vocabulary, which helps to critique, analyze, and compare eco-feedback designs. Finally, fourth, the design space is helpful in uncovering areas that have been underserved in research thus far, allowing researchers/designers to target areas that are potentially problematic and/or important.

7. The design, development, and evaluation of UbiGreen, an eco-feedback application to promote green transportation habits. In Chapter 5, we introduced *UbiGreen*, a novel eco-feedback application for mobile phones that semi-automatically senses and feeds back information on transportation routines and rewards green transit decisions. UbiGreen runs continuously in the background of the user's mobile device and updates the background display *(i.e.,* wallpaper) based on sensed transit. We created two versions of the display: a *tree design* that grows leaves, flowers and fruit, and an *arctic eco-system* that uses an ice floe and animals to represent green transit use.

To explore how a mobile eco-feedback system would be perceived, used, and experienced, we evaluated UbiGreen in a three-week field study with 12 participants. We found that participants enjoyed the unfolding narrative of the background display based on their actions in the real-world and that, to maintain anticipation, participants wanted new "stories" downloaded on their phones every week. UbiGreen was a *glanceable*, *ambient,* and fairly *artistic* display; this glanceability and ambience was appreciated. However, the display itself did not provide enough quantitative information for participants to track different types of transit patterns, so it was difficult for participants to see if they were making *greener* transit choices as the study progressed. In summary, participants were positive about the glanceability and aesthetic of the display but wanted more actionable information.

8. The design and evaluation of water usage feedback displays, studying specific dimensions of feedback (e.g., level of data granularity) as well as social and household context (e.g., issues of privacy). As the first work in the area of visualizing *disaggregated* water resource consumption data, Chapter 9 explored a broad range of novel eco-feedback designs through an online survey study with 651 participants and in-home interviews with 10 households. The goals were to examine and uncover particularly promising elements of the designs and to investigate how such detailed data may affect household dynamics.

Through the use of a basic bar graph design, we first evaluated design dimensions participants perceived as particularly useful for disaggregated water data (*e.g.,* temporal granularity at the level of day, week or month). We found widespread interest in displaying data at the *individual fixture level* with hot and cold information as well as the use of historic self-comparisons to contextualize usage over time. We then evaluated six design probes that integrated multiple dimensions and allowed us to examine more complex issues such as competition, motivation, and privacy. The design probes elicited strong and sometimes polarizing reactions. Although some designs provoked positive feelings of competition, accountability, and playfulness in many participants, for others, these same designs felt intrusive, blame-inducing, or antithetical to the goal of saving water. The key here is to realize that eco-feedback displays do not just visualize consumption, they also visualize *household activities*. Consequently, designers should take into account how their displays may affect underlying social dynamics in a household and how they expose otherwise latent routines. In addition, we found widespread interest in simple, glanceable designs.

10.2 DIRECTIONS FOR FUTURE RESEARCH

In this section, we cover the primary limitations of this dissertation to both better frame and scope our contributions as well as to highlight opportunities for future work. We also provide perspectives on the future of eco-feedback research based on our experiences. As with the section above, we split our discussion of limitations and opportunities for future work by contribution area: *foundational, sensing,* and *feedback.* We end with some general challenges and opportunities for eco-feedback technology.

10.2.1 Foundational Limitations and Future Work

For our foundational contributions, we used a multi-faceted approach to investigate personal transit and water usage attitudes, routines and perspectives. This included surveys, interviews, and *in situ* experience-sampling field studies. A key limitation, however, is the bias in our participant base. For each formative study participants had preexisting proenvironmental attitudes and beliefs. Thus, our findings relate more strongly to populations that self-identify with eco-friendly perspectives. An interesting area for future work, and one that has been rarely addressed in the HCI literature, is to study populations that are neutral or uninterested with regards to the environment and how this may influence the design of eco-feedback. The key questions here are: how to best engage these populations in environmentally relevant topics and how to leverage this knowledge in the design of eco-feedback technology.

A second opportunity for future work is in moving qualitative investigations outside of the single-family detached home and into different sites and contexts such as: multi-family homes *(e.g.,* apartment buildings), office buildings, and commercial buildings *(e.g.,* grocery stores, cafes, and retail centers). Although some *deployments* of eco-feedback technology have occurred outside of single-family residential spaces (*e.g.,* Siero *et al.,* 1996, Peterson *et al.*, 2007), few *formative* investigations have taken place that examine motivations for resource conservation in these areas.

We argue that these sorts of formative inquiries are important prerequisites before conducting field deployments of eco-feedback technology. Because of the resource intensiveness of eco-feedback field studies, it is paramount that researchers and designers familiarize themselves with the social, political, and environmental context of use before deployment. This can be achieved through ethnographic- or survey-based inquiries, through small, short-term deployments (such as we did with UbiGreen in Chapter 5) or via familiarization with relevant literature when available.

In addition, for each of these different deployment contexts (*e.g.,* residential vs. commercial building), there exist different tensions between a number of elements including: dweller control vs. third-party control (Pierce *et al.*, 2008), responsibility of payment for the resources, and different avenues and opportunities for understanding consumption in these contexts. Dillahunt and colleagues have explored some of these tensions directly by examining resource use in low-income housing (*e.g.,* Dillahunt *et al.*, 2009; Dillahunt *et al.,* 2010) but more work is needed. For example, how does the introduction of sub-metering into multi-family buildings change the perspectives and understandings of consumption among residents (*e.g.,* see Mayer *et al.,* 2004b)? And how do motivations, understandings, and perspectives of resource use change from the home to the workplace? Answers to these questions will help broaden the ways in which eco-feedback may be used to promote proenvironmental behaviors.

10.2.2 Sensing Limitations and Future Work

In this section, we discuss limitations and future work for sensing and inference systems for personal transportation and water usage.

10.2.2.1 Transit Sensing

Our personal transit sensing work had three primary limitations. First, although components of the underlying sensing system were evaluated in past work (*e.g.,* Lester *et al.*, 2005; Sohn *et al.*, 2006), the accuracy of the transit inference system itself was not independently validated via experimentation (*e.g.,* offline analysis with ground truth and sensor stream data). Instead, our validation extended from actual use of the UbiGreen application in pilot testing and field deployments. The primary metric of evaluation here, then, was the qualitative perceptions of the application's ability to accurately infer travel mode (a majority of participants were positive about it). To compensate for inaccuracies and limitations in the sensing system, UbiGreen provided self-report interfaces where participants could record their current transit activity.

Second, primarily as a reflection of when this research was conducted and the systems were built (circa 2007), our sensing system required a wearable device (the MSP) to operate. Because of its size and weight, the MSP was perceived as burdensome to wear (particularly for some clothing styles, *e.g.,* skirts). In addition, since it was external to the mobile phone, some participants forgot to put it on in the morning when they dressed (though UbiGreen's built-in warning system for this failure case was sufficient to prevent any of our participants from forgetting to wear the MSP throughout an entire day).

Third, again as a reflection of the time period when this work was undertaken, we did not use GPS in our transit inference algorithms. As highlighted in Chapter 2, much work has emerged since the development of UbiGreen, which could be integrated into future systems.

Looking forward, it is likely that any future personal transportation sensing and inference system will leverage *all* relevant sensors common now on mobile devices including accelerometers, GPS, digital compasses, and gyroscopes. This multi-modal sensor integration will likely improve transit inference accuracy and, perhaps, minimize training and calibration effort. However, as noted by Saponas *et al.* (2011), a major challenge faced by future human activity recognition systems is the battery life cost on the device. This is a significant issue because sensing and inference systems often require continuous operation to function. In UbiGreen, a person's current transit mode was constantly being tracked, which resulted in ~8-12 hours of battery life from the MSP and ~24-30 hours of battery life on the mobile phone. These sorts of battery lifetimes were acceptable for short field studies but are on the short-end for commercial systems. The very fact that eco-feedback systems require power is somewhat of a paradox as this, in itself, is consumption that affects the environment. This problem highlights the need for life-cycle analysis (Curran *et al.*, 2006) of eco-feedback systems. We return to this issue below in Section 10.2.4.

10.2.2.2 Water Usage Sensing

Our two empirical evaluations of HydroSense demonstrated promise for single-point sensing of disaggregated water usage via continuous monitoring of water pressure. Despite the algorithmic advancements we made in moving from controlled experiments (Chapter 7) to field deployments (Chapter 8), important areas of future work remain.

Evaluating HydroSense across a greater range of conditions and installation sites. HydroSense has been evaluated in 15 study sites (12 homes, 3 apartments). However, more work is needed to better define the strengths and weaknesses of the pressure-based approach across a broader range of homes and apartments. This research should document the installation location of the sensor, the type of plumbing system, house size, piping type (*e.g.,* PVC, PEX, copper, galvanized, or manifold), hot water heater type and size, as well as the presence and type of pressure regulator, "water hammer" dampeners, recirculating pumps, and water heater expansion tanks (which may dampen or attenuate the pressure transient signal). The key is to uncover if there are certain physical factors that lead to increases or decreases in HydroSense's performance.

Similarly, even within one study site, more work is needed to assess the advantages/disadvantages of various installation locations both in terms of their ease with which to install and power the HydroSense device as well as in terms of performance. Although we experimented with a variety of installation locations across our experiments in Chapters 7 and 8 including below bathroom sinks, kitchen sinks, hot water heaters, at utility faucet outlets, and exterior house bibs, we did not comprehensively examine the effect of sensor location within a single site.

For the above explorations, we would advocate that a more sophisticated form of our staged experiments in Chapter 7 be used rather than automated ground truth sensing networks because the latter is so resource-intensive, and the goal here is breadth of study across experimental sites. More particularly, we suggest that the ground truth data tables presented in Chapter 8 be used to guide the design of a more realistic staged water usage script including: compound and collision event testing at depths of two and three levels, at least five full laundry washes (ideally five full laundry washes on each laundry setting but this may be time prohibitive), at least five full dishwasher uses (again, ideally five full dishwasher uses on each setting), and the varied use of manually controlled valves including different temperature mixtures and flow rates. In addition, because many showers are bath/shower combinations, the diverter valve needs to be used to enumerate and test every possible combination of activations and deactivations (*e.g., diverter valve starting in bath position→bath on→diverter valve switched to shower→(8 minutes)→shower off* will result in a different pressure signature than *diverter valve starting in shower position→shower on→(8 minutes)→shower off* even though the correct inferred activity in either case is still "showering for 8 minutes"). Household interviews with home occupants are also important here to better understand different uses of water and common water usage activities within the home itself. In addition, demographic data similar to that discussed in Chapter 6 should be collected.

Given the above, however, staged experiments, no matter how sophisticated, will not be able to adequately collect data on certain features such as time of use and frequency of use. These contextual factors (and others) can only be gleaned through real-world deployments as we did in Chapter 8. Thus, a real-world field deployment evaluation of the sensing system with ground truth labels is the gold standard and, eventually, cannot be avoided. However, the choice to conduct a real-world evaluation depends on the research goals and the resources available. In the future, to mitigate costs, it may be possible to piggyback on pre-existing or planned water usage experiments where homes fixtures/appliances are already instrumented as appears to be the case in the Anglian Water experiments (see report: UK Parliament, 2000). However, if inline flow sensors are used for ground truth data collection, future research needs to explore what effect, if any, the presence of these sensors have on the pressure signal.

Evaluating event identification and segmentation with real-world water usage pressure data. A second limitation and area for future work involves evaluating *event identification* and *segmentation* approaches using real-world water usage data. Although our first experiments (Chapter 7) examined a full end-to-end algorithm including: event *identification*, *segmentation*, and *classification*, in our second set of experiments (Chapter 8), we evaluated the *classification* phase only. That is, we used *pre-segmented* pressure transients fed into our classification algorithms (*i.e.,* the start and end of waveforms were marked by the ground truth labels). This allowed us to focus solely on the *classifiability* and *consistency* of real-world water usage pressure events without potential complications from poor event identification/segmentation algorithm performance. However, by scoping our analysis in this way, we were unable to characterize the end-to-end performance of HydroSense with real-world water usage data.

With that said, the original HydroSense work segmented staged water usage data with 100% accuracy, so segmentation of real-world data should be possible. The primary challenge will be properly segmenting compound and collision events, particularly in apartments where noisier pressure signals are possible because of crosstalk between apartments. As noted in Chapter 8, the *classification* and *segmentation* tasks could even be combined to increase robustness to sources of ambiguity such as transient collisions because many statistical signal processing strategies become sub-optimal after separating segmentation and classification. Future work is necessary to determine the best strategy for event identification, segmentation *and* classification, but our work in Chapters

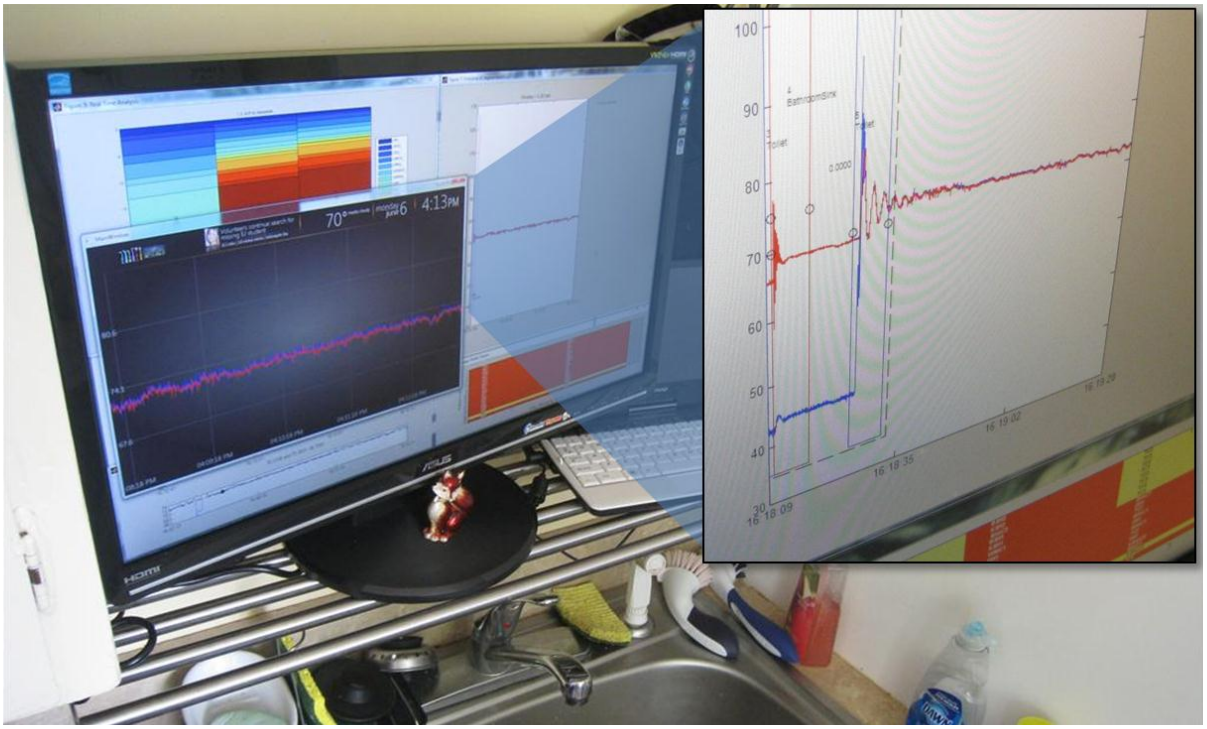


Figure 10.1: A real-time end-to-end HydroSense system with event identification, segmentation, and classification. The monitor is displaying Matlab visualizations of different aspects of our algorithm with a C#-based visualization in the foreground (black window). The segmentation boundaries and inferred events are visible in the magnified inset.

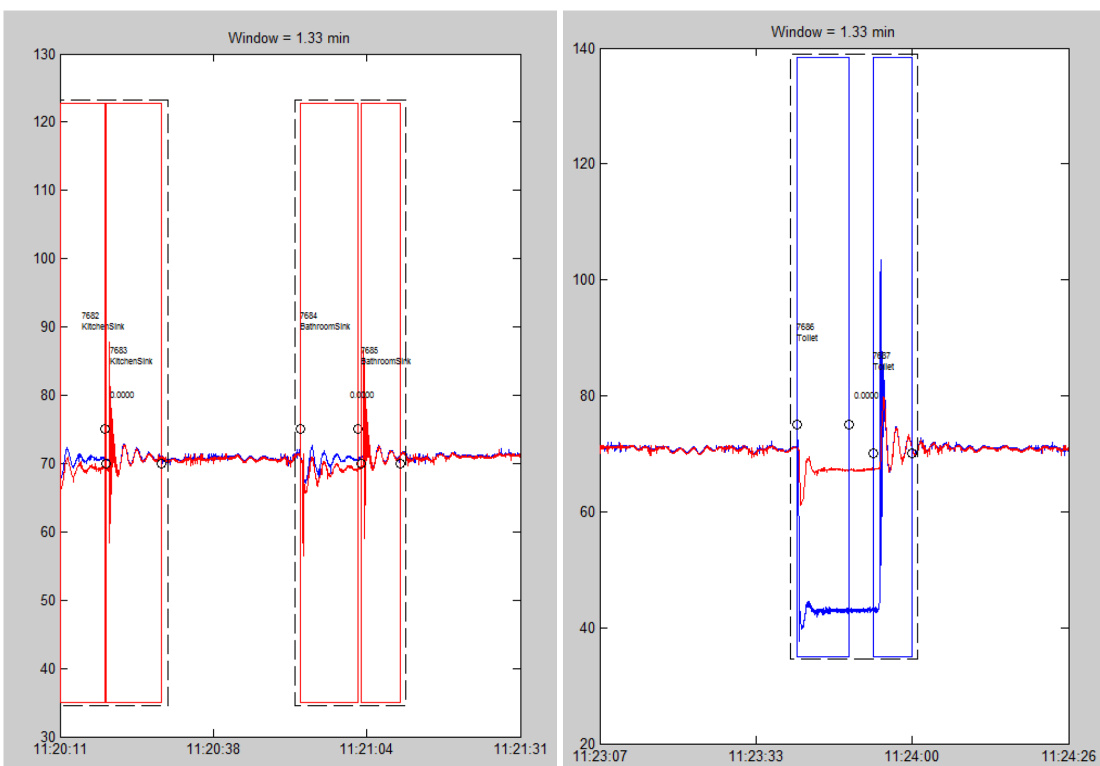


Figure 10.2: Magnified views of the real-time HydroSense end-to-end algorithm with event identification, segmentation and classification. Future work is needed to refine and evaluate this system.

7 and 8 provide a solid foundation for moving forward. We are currently implementing a real-time HydroSense system, which integrates a full, end-to-end algorithm (Figure 10.1 and Figure 10.2). However, this work is still in preliminary stages and not yet evaluated.

Exploring a greater range of water-usage features, feature selection techniques, and methods to join various knowledge sources. Although we used a number of features in our classification algorithms including template-based features, transient-based features, transition-probability features, and paired-valve features (such as water usage duration), there is a much larger feature space to explore including contextual features (time of day or day of week) and more emphasis on smoothed pressure-delta related features (*e.g.,* similar to flow-trace analysis, see Chapter 2). Figure 10.3 highlights a list of potential classification features but there are likely even more. We note again that some features can only be evaluated using real-world water usage data. For example, staged experimental data is insufficient to explore how temporal features may impact classification.

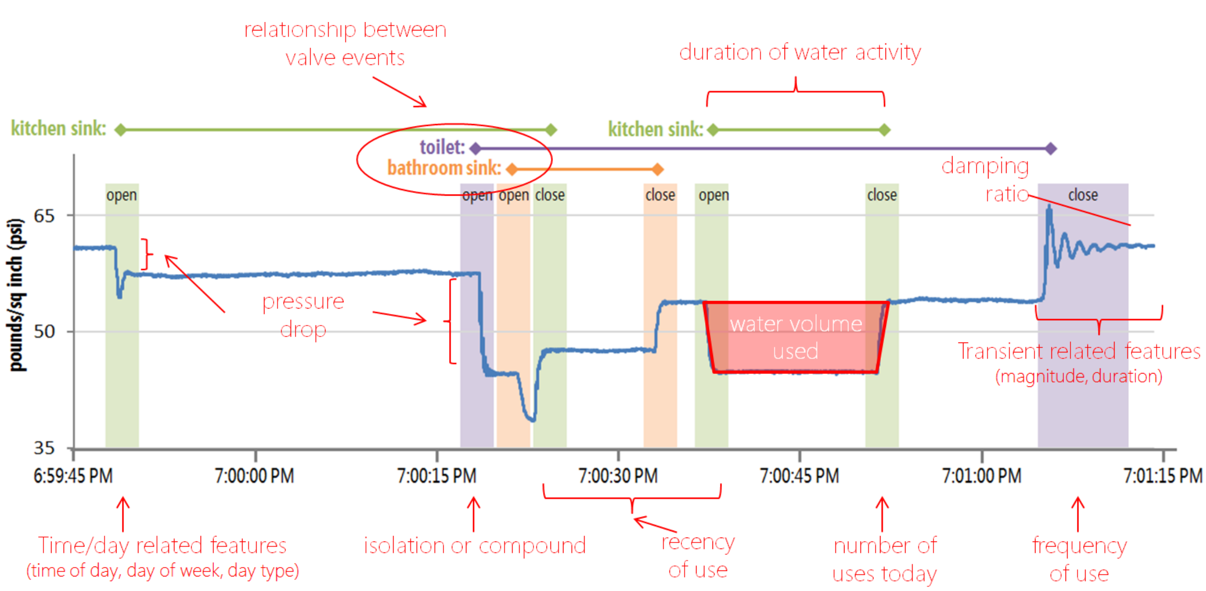


Figure 10.3: A one minute, 30 second pressure stream trace from our longitudinal deployment in Chapter 8 with red textual annotations describing possible classification features.

In addition to investigating new features, more work needs to be done with regards to *how* these features are selected and combined; our Bayesian model applied equal weighting to all features and terms. Future algorithms may also want to explore a combined Bayesian and hierarchical model approach where, for example, compound transients are handled differently than transients that occur in isolation. Additionally, our Bayesian model is trained to fit the data (*i.e.,* a generative algorithm), but more discriminative algorithms such as conditional random fields (CRFs), may be more appropriate for classification tasks (*i.e.,* trained to fit separate classes in the data). We are actively investigating discriminative classifiers like CRFs to better quantify relationships in the data and flesh out complicated relationships among potential features.

Deeper evaluation of pressure-based flow inference. Most of our work focused on using pressure to *classify* water usage events but not to infer the amount of water used by those events. Although we investigated water flow rate inference in Chapter 7, this investigation was limited to four homes and staged experimental data under fairly constrained conditions: isolated events, near-maximum flow rates out of fixtures, only one temperature setting, and only in single-family detached homes (note: we could not evaluate flow in Chapter 8 as our ground truth sensors were not capable of recording flow rate information). Our flow-rate inference algorithm was also fairly simplistic: a straightforward linear regression model. However, as pointed out in Chapter 7, water flow in a typical plumbing system is laminar, turbulent, and sometimes a mixture of both. In each of these flow states, the governing equation between pressure and flow is different, and when the flow state changes from one mode to another, the relationship between flow and pressure-based features can be discontinuous. Consequently, more sophisticated flow inference models may be needed to handle these complications. In addition, more work is needed to evaluate the amount of training data necessary to reach flow rate calculations on par with traditional water meters.

One potential direction here may simply be to combine data from a standard water meter (where flow rate information is basically free) along with a pressure-based sensing system. This combination could not only improve the quality of flow-rate information but also in disaggregation accuracy (features from the water meter could aid in classification). Smart meters could be used if their data is accessible; otherwise traditional water meters can often be non-intrusively instrumented from the outside using Hall Effect sensors (see Chapter 2)

Future work is also needed to examine pressure-based flow calculations in different building settings (*e.g.,* multi-family homes) and under varied flow rate and temperature settings for each fixture. Finally, although Chapter 8 explored differentiating between hot and cold water activations, we did not explore if HydroSense can differentiate between the *amount* of hot and cold water used and the number of pressure-sensors required to achieve reasonably good accuracy.

Exploring techniques to ease the calibration burden. The cost and ease of installing HydroSense, including any required training or calibration, will directly impact its adoption. Our algorithms require a database of labeled water usage templates (signatures) for each home, which means the user must activate and deactivate each fixture or appliance multiple times[35] (to create a template) and provide a text (semantic) label for each activation (*e.g.,* "upstairs shower" or "downstairs toilet"). Although initially burdensome, the calibration process should be necessary only once at installation and, perhaps, updated when a new fixture or appliance is installed. In either case, a mobile device such as a tablet or phone could run "training software" that guides the user in this process and serve as an interface for collecting text labels.

Of course, this level of calibration is required only if the fixture or appliance's disaggregation signature is different among homes. Unfortunately, based on our research, the shape of the water transients used by HydroSense appear to be affected by the plumbing layout of the home, making it unlikely that template signatures can be easily shared across homes. Indeed, in preliminary analysis we found little correlation between transient signals for similar fixture types across homes. Future work is needed to derive what aspects of the water pressure signal, if any, are invariant to a home. For example, water usage durations and relative pressure drops are much more robust cross-home signatures than the pressure transients themselves—*e.g.,* a bath has a larger pressure delta than a shower when activated, while both have larger pressure deltas than a faucet. If particular features are identified as home invariant, a distributed crowd-sourcing approach for signature labeling could be used. Recently, researchers have begun exploring opportunities for cloud-based and crowd-sourced classification models (*e.g.,* Lane *et al.*, 2011). However, we are unaware of any past work that attempts to share water usage signatures to ease calibration.

Future work could also look at the feasibility of an unsupervised classification approach that does not require a user-created database of signatures and labels. Instead, such a system would learn signatures over time and acquire the labels later from the user by employing a carefully designed labeling interface. For example, the eco-feedback system might state, "The second-most water consuming fixture/appliance in your home has yet to be labeled. We think it's the master bathroom toilet, which was last flushed 5 minutes ago. Is this correct?" In this way, the calibration effort would be amortized over a longer time. Roberts and Kuhns (2010) are in the early stages of evaluating an electricity-based disaggregation system that uses an unsupervised learning approach combined with

[35] In fact, it is currently unclear exactly how much training data is necessary from each fixture/valve to reach reasonable levels of accuracy. We ran an "amount of training data" experiment on the five deployment sites in Chapter 8; however, this experiment was setup to test *days* of data necessary for training (so it more closely parallels a semi-supervised learning approach) rather than the number of samples necessary from each fixture/appliance. This is an open area for future work.

user intervention to provide semantic labels, but we are unaware of similar work for water-based disaggregation.

Other classification and inference areas to explore. A number of other areas are worth exploring, such as: applying HydroSense to detect leaks, evaluating HydroSense's ability to classify outdoor water usage, and combining a meter-based flow-trace approach with HydroSense to boost disaggregation and flow inference performance. As flow-trace analysis (see Chapter 2) is the closest disaggregation sensing technique to HydroSense, future work should also empirically compare and contrast these two approaches more directly.

Applications of HydroSense beyond eco-feedback. Although this dissertation focused specifically on sensing to support eco-feedback on residential water usage, HydroSense has application to other areas as well. I will discuss two here: *health applications* and *urban informatics* applications.

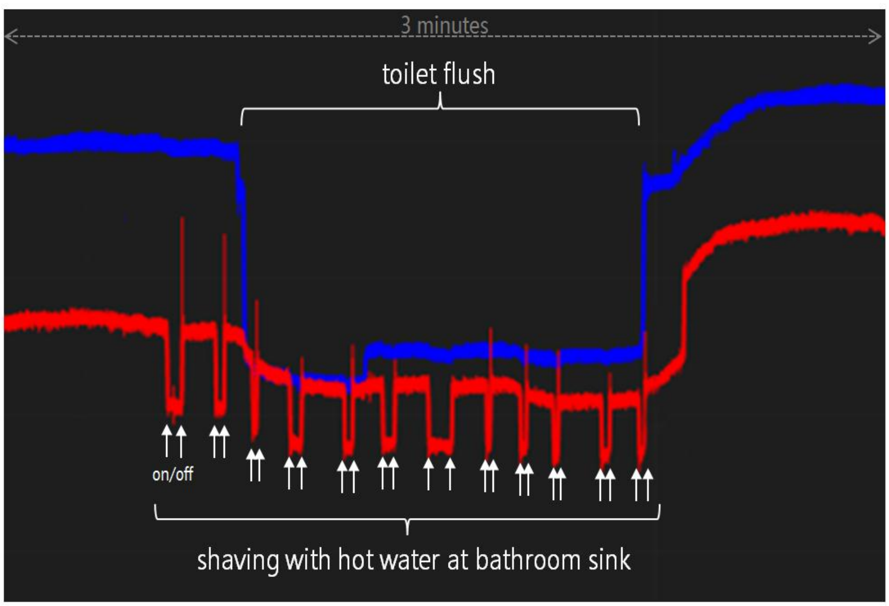


Figure 10.4: Future applications of HydroSense could attempt to infer higher level activities from water usage, which may aid assistive care applications. This figure shows a water usage pattern of a man shaving, which was taken from A1 in our real-world dataset from Chapter 8. The red pressure stream is the hot water line, the blue pressure stream is the cold water line.

Low-cost and easy-to-install methods to monitor activity for elder care and assisted living applications have long been a focus of Ubicomp and HCI research. As the baby boomer population ages, this focus is likely to receive even more attention. Because water is fundamental to many activities of human life (*e.g.,* bathing and cooking), sensing disaggregated water usage should be a useful proxy for monitoring activities of daily living.[36] As a first step, we plan to analyze and explore patterns of water usage in the longitudinal dataset we collected in Chapter 8. One goal is to see if we can use water usage inference to build models of higher level activities (*e.g.,* cooking in the kitchen, shaving in the bathroom). As an example, Figure 10.4 shows a potentially identifiable pattern of a man shaving: a series of quick on/off water usages (12 times) at the bathroom sink.

Figure 10.5: HydroSense can be used for applications beyond eco-feedback. For example, in this figure, disaggregated water usage is used in an envisioned assistive care application to automatically alert care givers to a potentially health threatening situation.

Another one of our goals is to build water usage models to detect anomalous activity. An assistive care application, for example, could use this model to automatically detect when a person has not been following his/her morning routine (*e.g.,* no bathroom water activity) and take appropriate action (*e.g.,* alert a care provider). See, for example, Figure 10.5. We are also interested in investigating whether patterns in water usage can reveal issues with dementia (*e.g.,* forgetting to flush the toilet or maintain proper hygiene is a common symptom) and to support studies of health and hygiene practices (*e.g.,* looking at patterns of toilet and faucet usage, see: Wilkes, 2005). These potential directions are all enabled by disaggregated water usage sensing. Of course, these scenarios also re-emphasize the importance of privacy and security around disaggregated water data as it can be used to derive much information about a home and the activities therein.

[36] Health professionals often use the ability or inability to perform activities of daily living as a measurement of the functional status of a person.

A second potential application area is in urban informatics. Urban informatics is the study and design of new urban experiences enabled by an increasingly digital environment (Foth, 2009). In this dissertation, we explored individual household uses of HydroSense but there is also the opportunity to sense patterns of use across the city by uploading data to a central repository (Figure 10.6). Water suppliers could use this information to better target and evaluate their conservation campaigns (*e.g.,* determine how many households actually used the mailed low-flow fixture rebates and the effect this has on water usage). Even anonymous data could aid water suppliers in creating better demand prediction models and governments in mandating new types of plumbing codes and low-flow fixture regulations. Websites could provide interactive visualizations that allow interested citizens to gain a different perspective on water use and water infrastructure in their city.

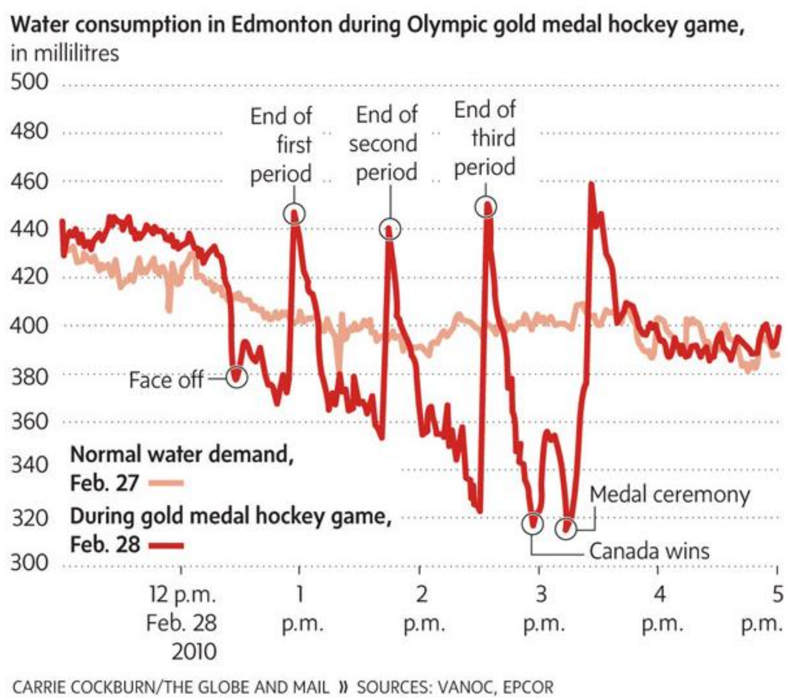


Figure 10.6: Sensing resource use on a collective scale can reflect new insights into the pulse and rhythm of a city. For example, this figure, released by EPCOR, the water utility in Edmonton, Canada, shows water usage during the 2010 Olympic gold medal hockey game between Canada and the United States. It appears that many Canadians timed their trips to the bathroom to correspond with breaks in the game (*i.e.*, between periods).

10.2.3 Feedback Limitations and Future Work

We transition now to our last limitations and future work section. Rather than break-up this section to individually address limitations in transit and water usage feedback (as we did with the sensing work above), we combine the discussion of both here.

Evaluation methodology. While the goal of our feedback evaluations was to provide a solid foundation for designs to be used in future behavioral intervention trials, we did not conduct such trials ourselves. As discussed in Chapters 1, 3 and 4, behavioral intervention trials require a great deal of time, personnel resources, and cost. Thus, we have argued that it is of great importance, and one of the HCI/Ubicomp community's strengths, to apply an iterative design process to evolve and polish feedback designs before such studies are undertaken. Our evaluations, for example, identified a number of important interface elements that designers should consider in any eco-feedback design including *actionability*, *motivational strategies*, *simplicity*, and a balance between *pragmatic* and *artistic* representations of information. Our hope is that the eco-feedback designs presented in Chapters 5 and 9 can be iterated upon based on our findings, then deployed and evaluated in behavioral intervention trials in collaboration with environmental psychologists. These longitudinal deployments are necessary to answer questions such as: which designs or design elements are most effective at impacting behavior? What sort of novelty effects exist? Once deployed, how are the eco-feedback systems perceived in terms of revealing private information either to members of the household or to guests/visitors? Do these findings differ from this dissertation's survey and interview findings?

To begin to address these issues, we have deployed an eco-feedback system for water usage in two researchers' homes (see Figure 10.7; based on Chapter 9). Reactions from the four adult household members suggest that the display has a noticeable effect in making otherwise obscure household activities visible (*e.g.,* a late-afternoon shower indicates one person has gone for a run) and that some display locations may feel more intrusive than others (*e.g.,* bathroom *vs.* kitchen). In addition, because HydroSense is a *probabilistic* sensing system, household members in both homes observed errors in the display. This issue suggests that representing confidence margins in the display may be useful, and highlights the need to determine to what degree, if any, users will accept inaccurate inferences in eco-feedback or are willing to intervene and correct inaccuracies. Future deployments are needed to explore these reactions and perceptions more deeply.

Figure 10.7: Prototype disaggregated water usage eco-feedback displays running in a researcher's (a) kitchen and (b) bathroom. These systems have been running intermittently in two researchers' homes for multiple months to debug the real-time sensing system, iterate on visual designs, and study *in situ* reactions to the displays.

Study sample. As already mentioned in the foundational limitations section, most of our study participants were biased towards proenvironmental attitudes and beliefs. At worst, this limits our findings and implications to a narrower population: namely, those interested in the environment (though our sample likely represents early adopters of eco-feedback systems and thus offers a relevant perspective). In the future, it is important to extend our work to other types of study populations (*e.g.,* those with neutral or negative environmental attitudes). We note, however, that certain findings will likely extend to more general user populations. We would expect those designs that tested poorly with self-interested participants will likely also not perform well on a neutral or disinterested population.

An additional area of future work here is to compare and contrast eco-feedback techniques and designs across different cultures and regions of the world. For example, a well-known finding in cross-culture personality research is that Westerners (*e.g.,* Americans) tend to be more individually oriented and that Easterners (*e.g.,* Chinese) tend to be more socially oriented (Yang, 1986). A potential implication is that eco-feedback designs that focus on social groups or the larger collective may be a more effective motivator of pro-environmental behavior for Eastern individuals than their Western counterparts. A second example involves the ways in which Western and Eastern cultures tend to react to feedback about the self. In an experiment conducted by Heine *et al.* (2001) participants from various cultural backgrounds received negative feedback about their performance on a task. Whereas North Americans tended to discount the significance of the negative feedback, the Japanese were highly responsive and showed evidence of reduced confidence in their ability to perform tasks similar to the experimental task. These sorts of findings demonstrate a need to think about and study cross-cultural differences in attitudes and behaviors related to the environment as well as in how eco-feedback systems may be perceived and understood.

10.2.4 General Challenges and Opportunities for Eco-Feedback Research

A full life-cycle assessment of an eco-feedback system. For eco-feedback to be successful, it must result in a net reduction of environmental impact, including the cost of the manufacturing and distribution of the eco-feedback system, the energy used by the system over its lifetime, and the environmental impact of the eventual disposal of the device. This analysis is critically important, yet we are unaware of any eco-feedback work that takes it into account. Eco-feedback systems should be designed to be low power and with "green" materials, though admittedly these are two challenging design and engineering tasks. For HydroSense, we recently published preliminary work on a self-powered version called WATTr (Campbell *et al.*, 2010). Another potential approach is simply to adopt existing systems for eco-feedback. With UbiGreen, for example, the primary interface was a standard mobile phone. Tools such as Bonnani *et al.*'s (2010) SourceMap, which relies on crowd sourcing to perform lifecycle assessment, could also be used in conjunction with eco-feedback pursuits.

An (over)focus on the individual? Much eco-feedback research has focused on how to inform or modify *individual behaviors* that directly affect the environment. Individual actions have the potential to translate to much larger impacts, for example, in voting or participating in proenvironmental movements (Stern, 2000b) or when individuals influence the actions of organizations to which they belong—*e.g.,* engineers may choose to use environmentally benign materials, designers may emphasize the material lifecycle of their products. The CHI 2011 Sustainability Panel (Khan *et al.*, 2011) attempted to further highlight this opportunity by examining ways in which HCI can target users beyond the end-consumer such as designers, architects, urban planners or even the construction workers and consider interfaces and interactions that support sustainable design, manufacturing and construction. This is eco-feedback on a broader scale, demonstrating the impact of organizational, political, or building decisions on the environment.

Surveillance and regulation. In Chapter 9, we found that some participants reacted negatively to certain visual designs because they felt overly intrusive. Eco-feedback systems that sense and feedback *disaggregate* resource use are particularly susceptible to abuse because of the amount of information that is revealed about activities in the home. As Dourish (2010) notes, "technologies designed to monitor and record actions, particularly with respect to their environmental consequences, are clearly also a natural path for various forms of surveillance and regulation." Thus, security and privacy need to be important components of future system design.

Moving towards the ideal eco-feedback system. The ideal eco-feedback system will likely be one that requires the least amount of effort and time to use. Eco-feedback designers should consider not just the best ways of representing consumption data but also how this data can be analyzed and used to recommend the best actions to take for the least amount of effort to reduce a person's environmental footprint. These suggestions should be personalized based on the sensed activities of the individual and, perhaps, their demographics. In addition, in the case of home resource consumption, the eco-feedback display should not be seen in isolation but rather as a larger part of a home automation network that can automatically control devices and appliances in the home to increase efficiency.

10.3 FINAL REMARKS

We are at the precipice of a new era of computing; one where small sensors, sophisticated machine learning algorithms, and new types of interfaces will render otherwise latent patterns in our lives visible. These sensing and feedback systems will empower their users by providing new insights into the impacts of their behaviors on their health and the environment around them. As designers and HCI/Ubicomp researchers, it is our role to help define the future of these systems and determine the most effective strategies for sensing and feedback. One lingering challenge is how to reconcile all of these information sources to limit attentional demand. In this way, eco-feedback systems of the future should not simply be feedback systems, but rather, personalized recommendation engines guiding us to minimize our environmental footprint.

Finally, eco-feedback is but one tool to effect change. Environmental sustainability is a complex, global problem that will require a combination of technical, behavioral, political, and socio-economic solutions. Although most eco-feedback work, including our own, has focused on informing individual action, the true power of eco-feedback may ultimately be in the cascading effects of those actions on influencing larger-scale cultural change.

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Appendix A.
References Used for Comparative Eco-Feedback Review

The following list of references was used for the comparative review of eco-feedback research presented in Chapter 3.

HCI/Ubicomp Papers Discussing Eco-feedback

First Author	Paper Title	Venue	Paper Type	Year	Eco-Feedback?	Artifact	Primary Visual Representation	Study
Al Mahmud, A.	iParrot: Towards Designing a Persuasive Agent for Energy Conservation	Persuasive	Short	2007	Yes	Embodied Intelligent Agent	Embodied Agent	Yes, laboratory study to measure subjective response
Aoki, P.M.	A vehicle for research: using street sweepers to explore the landscape of environmental community action	CHI	Full	2009	Yes, citizen science			
Arroyo, E.	Waterbot: Exploring Feedback and Persuasive Techniques at the Sink.	CHI	Full	2005	Yes	Ambient Artifact Prototype	Ambient	Yes, qualitative laboratory evaluation
Bang, M.	The PowerHouse: A Persuasive Computer Game Designed to Raise Awareness of Domestic Energy Consumption	Persuasive	Full	2006	Yes, virtual	Desktop Computer Game	Game	No
Bang, M.	Promoting New Patterns in Household Energy Consumption with Pervasive Learning Games	Persuasive	Full	2007	Yes	Mobile Phone Game	Game	No
Bray, R.	Informative Smart Green Office Buildings	UbiComp	Workshop	2007	Yes	Ambient Displays in Office Buidling	Not disclosed	No
Brewer, R.S.	Carbon Metric Collection and Analysis with the Personal Environmental Tracker	UbiComp	Workshop	2008	Yes	Proposed Carbon Tracker	Not disclosed	No
Chen, Z.C-L.	Live Sustainability: A System for Persuading Users Toward Environmental Sustainability	UbiComp	Workshop	2008	Yes	Proposed website to track CO2	Website	No
Chetty, M.	Getting to Green: Understanding Resource Consumption in the Home	UbiComp	Full	2008	Yes, essay			
Dada, A.	The Potential of UbiComp Technologies to Determine the Carbon Footprints of Products	Pervasive	Workshop	2008	Yes, product lifecycle	Mobile Phone Prototype Application	Text	No
Dillahunt, T.	Motivating Environmentally Sustainable Behavior Changes with a Virtual Polar Bear	Pervasive	Workshop	2008	Yes	Flash-based virtual polar bear	Abstract (polar bear)	Yes
DiSalvo, C.	Nourishing the ground for sustainable HCI: considerations from ecologically engaged art	CHI	Full	2009	Yes, essay			
Dourish, P.	Points of Persuasion: Strategic Essentialism and Environmental Sustainability	Pervasive	Workshop	2008	Yes, essay			
Fitzpatrick, G.	Technology-Enabled Feedback on Domestic Energy Consumption: Articulating a Set of Design Concerns	IEEE Pervasive Computing	Magazine	2009	Yes, essay			
Froehlich, J.	Sensing Opportunities for Personalized Feedback Technology to Reduce Consumption.	CHI	Workshop	2009	Yes, essay			
Froehlich, J.	UbiGreen: investigating a mobile tool for tracking and supporting green transportation habits	CHI	Extended abstracts	2009	Yes	Mobile Phone Ambient Display	Abstract (Tree and Polar Bear)	Yes, primarily qualitative
Gartland, A.A.	Weigh your waste: a sustainable way to reduce waste	CHI	Extended abstracts	2009	Yes	Interactive touchscreen for garbage history	Interactive Touchscreen	Yes, qualititative evaluations
Grevet, C.	Workshop on Defining the Role of HCI in the	CHI	Workshop	2009	Yes, essay			

	Challenges of Sustainability: Position Paper							
Gustafsson, A.	The power-aware cord: energy awareness through ambient information display	CHI	Extended abstracts	2005	Yes	Ambient Artifact Prototype	Ambient	Yes, qualitative laboratory evaluation
Gyllensward, M.	Visualizing Energy Consumption of Radiators	Persuasive	Short	2006	Yes	Ambient Artifact Prototype	Ambient	Yes, qualitatative interviews
Ham, J.	Can Ambient Persuasive Technology Persuade Unconsciously? Using Subliminal Feedback to Influence Energy Consumption Ratings of Household Appliances	Persuasive	Extended abstracts	2009	Yes	Embodied Virtual Agent	Embodied Agent	Yes
He, H.A.	Motivating Sustainable Energy Consumption in the Home.	CHI	Workshop	2009	Yes, essay			
Hickey, S.	Using Feedback to Enhance Use Phase Efficiency of Personal Computers	IEEE Symposium on Electronics and the Environment	Full	2009	Yes	Computer Widget	Graph and star rating	No
Hill, D.	The New Well-Tempered Environment: Tuning Buildings and Cities	Pervasive	Workshop	2008	Yes	Proprosed Feedback Interfaces for Buildings	Not Disclosed (proposed system in text)	No
Holmes, T.	Eco-visualization: combining art and technology to reduce energy consumption	Creativity and Cognition	Full	2007	Yes	Ambient Eco-Visualizations	Ambient	No, art project deployment
Holstius, D.	Infotropism: Living and Robotic Plants as Interactive Displays	DIS	Full	2004	Yes	Ambient Artifact Prototype	Abstract (an actual plant!)	Yes, both qualitative and quantitative
Hooker, B.	The Pollution e-Sign	UbiComp	Workshop	2007	Yes	Ambient Artifact Prototype	Ambient	Yes, three public site field tests
Kappel, K.	"show-me": water consumption at a glance to promote water conservation in the shower	Persuasive	Full	2009	Yes	Ambient Artifact Prototype	Bar Graph	Yes
Khan, O.	Promoting Environmentally Sustainable Behaviors Using Social Marketing in Emerging Persuasive Technologies	Pervasive	Workshop	2008	Yes, essay			
Kim, J-W.	The Tenere: Design for Supporting Energy Conservation Behaviors	CHI	Extended abstracts	2009	Yes	Small Ambient Screen at Power Outlet	Abstract (tree that changes based on energy usage)	No
Kim, T.	Coralog: use-aware visualization connecting human micro-activities to environmental change	CHI	Extended abstracts	2009	Yes	Ambient Computer Widget	Abstract (Coral Reef)	Yes, primarily qualitative
Lin, H-C.	GreenSweeper: A Persuasive Mobile Game for Environmental Awareness	UbiComp	Workshop	2008	Yes	Game	Game	No
Ljungblad, S.	Everyday Visualization to Support a Sustainable Development	UbiComp	Workshop	2007	Yes	Proposed vision		No
Loke, S.W.	Context-Aware Pervasive Persuasive Systems for Managing Water and Energy Usage, and CO2 Emissions: Multi-Levelled Policies, Goals, and an Expert Systems Shell Approach	Pervasive	Workshop	2008	Yes, essay			
Luther, K.	Pathfinder: an online collaboration environment for citizen scientists	CHI	Full	2009	Yes, citizen science			
Mankoff, J.C.	Environmental sustainability and interaction	CHI	Extended abstracts	2007	Yes, essay			
Mankoff, J.C.	Leveraging Social Networks To Motivate Individuals to Reduce their Ecological Footprints	HICSS	Full	2007	Yes	Proposed Carbon Tracking Social Network	Website	No

Mathew, A.	Using the environment as an interactive interface to motivate positive behavior change in a subway station	CHI	Extended abstracts	2005	Yes	Proposed Ambient Systems to Motivate Transit	Ambient	No
McCalley, T.	Persuasive Appliances: Goal Priming and Behavioral Response to Product-Integrated Energy Feedback	Persuasive	Short	2006	Yes	Lab Simulation	Slides (*e.g.,* conservation tips)	Yes, laboratory
Midden, C.	Using persuasive technology to encourage sustainable behavior	Pervasive	Workshop	2008	Yes, essay			
Oakley, I.	Motivating Sustainable Behavior	UbiComp	Workshop	2008	Yes, essay			
Odom, W.	Social Incentive & Eco-Visualization Displays: Toward Persuading Greater Change in Dormitory Communities	OZCHI Workshop	Workshop	2008	Yes	Feedback website for dorm's resource consumption	Website	Yes
Paulos, E.	Jetsam: Exposing our Everyday Discarded Objects	UbiComp	Extended abstracts	2006	Yes	Ambient Artifact Prototype	Ambient	Yes, qualitative deployment in city
Paulos, E.	Ubiquitous Sustainability: Citizen Science & Activism	UbiComp	Workshop	2008	Yes, citizen activism			
Paxton, M.	Participate: Producing a Mass Scale Environmental Campaign for Pervasive Technology	Pervasive	Workshop	2008	Yes	Mobile Phone Game Proposed	Not disclosed: game elements	No
Petersen, D.	WattBot: a residential electricity monitoring and feedback system	CHI	Extended abstracts	2009	Yes	Website Prototype	Bar Graph	Yes, website prototype evaluation
Pierce, J.	Energy Aware Dwelling: A Critical Survey of Interaction Design for Eco-Visualizations	OZCHI	Full	2008	Yes, essay			
Pousman, Z.	The Design of Imprint: "Walk the Walk" and Other Lessons	Pervasive	Workshop	2008	Yes	Touch screen display above printers (public)	Graphs (bar, pie, stripmap) and numbers	Yes
Ravandi, M.	Development of an Emotional Interface for Sustainable Water Consumption in the Home	HCII	Full	2009	Yes	Ambient Display (LCD) Prototype	Real-time & historical feedback; "emotional design"	No
Reitberger, W.	The PerCues Framework and Its Application for Sustainable Mobility	Persuasive	Short	2007	Yes	Proposed Mobile Phone Visualization	Numeric and Abstract Data	Yes, laboratory study using paratype method
Shiraishi, M.	Using individual, social and economic persuasion techniques to reduce CO2 emissions in a family setting (Eco-Island)	Persuasive	Full	2009	Yes	Ambient Display (for living room) and Website	Game with CO2 tracking	Yes, both qualitative and quantitative
Sohn, M.	Designing with unconscious human behaviors for eco-friendly interaction	CHI	Extended abstracts	2009	Yes	Set of Proposed Feedback Ambient Feedback artifacts	Ambient	No
Stein, J.	TerraPed: A Design Concept for Sustainability	Pervasive	Workshop	2008	Yes	Website Concept	A variety (it's a website); basic visual portrayal is footprint	No
Strengers, Y.	Challenging Comfort & Cleanliness Norms through Interactive In-Home Feedback Systems	Pervasive	Workshop	2008	Yes	EcoMeter	Line graphs	Yes, ethnographic of people using EcoMeter
Stringer, M.	Kuckuck – Exploring Ways of Sensing and Displaying Energy Consumption Information in the Home	UbiComp	Workshop	2007	Yes	Computer Interface for Electricity Usage	Line graphs	Yes, one household
Tomlinson, B.	Prototyping a Community-Generated, Mobile Device-Enabled Database of Environmental Impact Reviews of Consumer Products	HICSS	Full	2008	Yes, product lifecycle	Mobile Phone Prototype Application	Website and Mobile	Yes, actual deployment
Xiao, J.	PrintMarmoset: redesigning the print button for	CHI	Short	2009	Yes	Prototype: browser extension	Casual information visualizations	Yes, laboratory

	sustainability						(vague description: track print jobs and paper consumption over time)	
Yun, T-J.	Investigating the impact of a minimalist in-home energy consumption display	CHI	Extended abstracts	2009	Yes	Two Ambient Artifact Prototypes	Bar Graph	Yes, quantative and qualitative
Zapico, J.L.	Climate persuasive services: changing behavior towards low-carbon lifestyles	Persuasive	Full	2009	Yes, essay			

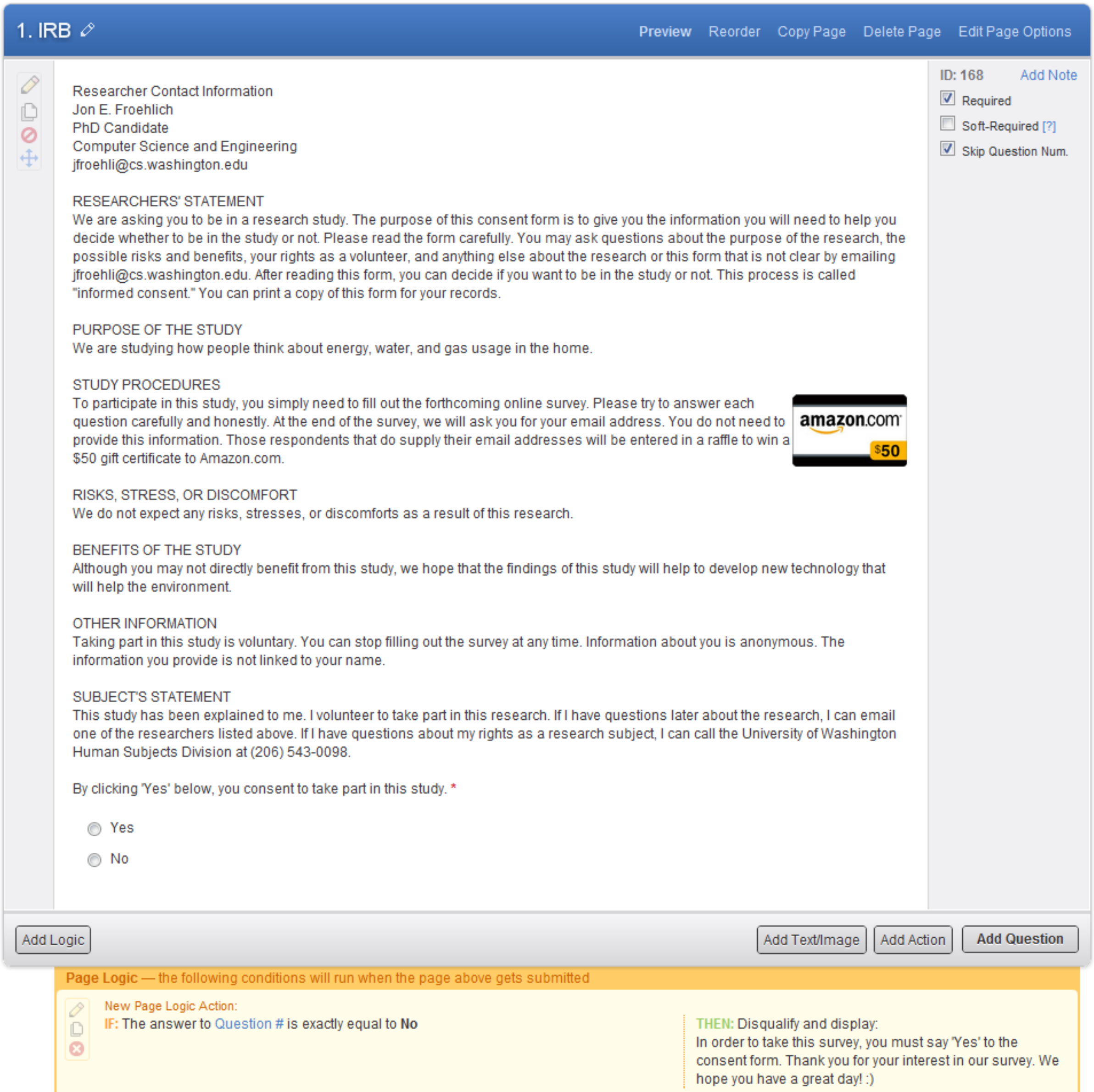
Environmental Psychology (and Related) Papers Using Eco-feedback Technology

Citation	Year	Number of Groups	Num Participants	Study Conditions	Study Duration	Resource	Compared To	Device Type
Brandon, G. and Lewis, A. (1999). Reducing household energy consumption: a qualitative and quantitative field study. *Journal of Experimental Psychology*, 19, 58-74.	1999	7 groups (N=120): 1. Self vs. others comparison (N=~17) 2. Self vs. self (N=~17) 3. Financial values (N=~17) 4. Environmental values (N=~17) 5. Leaflet presentation (N=~17) 6. Electronic feedback (N=~17) 7. Control (N=~17)	120	7	~9 mos	Electricity	Previous year over same time frame from utility data (weather corrected)	PC
Dobson, J.K. and Griffin, J.D.A. . (1992). Conservation effect of immediate electricity cost feedback on residential consumption behavior. *Proceedings of the ACEEE 1992 Study on Energy Efficiency in Buildings*, 33-35.	1992	3 groups (N=100): 1. Contact control (N=~33) 2. Blind control (N=~33) 3. Electronic feedback (N=~33)	100	3	2 mos	Electricity	Previous year over same time frame from utility data (weather corrected)	PC
Hutton, R.B., Mauser, G.A., Filiatrault, P., and Ahtola, O.T. (1986). Effects of cost-related feedback on consumer knowledge and consumption behavior: A field experimental approach. *Journal of Consumer Research*, 13(3), 327-336.	1986	4 groups (Quebec, N=271; BC, N=277, CA, N=236): 1. Electronic feedback (Q=92, BC=93, CA=95) 2. Education (Q=95, BC=92, CA=76) 3. Control (Q=84, BC=92, CA=65) 4. Blind control (N/A)	784	4	12 mos baseline 12 mos intervention 12 mos post-intervention	Electricity and Gas	12 months of baseline data prior to intervention	LED Display with buttons for mode switching
Keirstead, J. (2008). Behavioural responses to photovoltaic systems in the UK domestic sector. *Energy Policy*, 35, 4128-4141.	2007	1 group (N=118 but 91 responded) and 63 interviews	91	N/A	Questionnaires	Electricity		1 line LCD display
Kohlenberg, R., Phillips, T., and Proctor, W. (1976). A behavioral analysis of peaking in residential electrical-energy consumers. *Journal of Applied Behavior Analysis*, 9(1), 13-18.	1976	N = 3	3	3	3 months 2 weeks baseline 2 weeks information instructions 2 weeks feedback 2 weeks baseline 2 weeks incentive w/ feedback 2 weeks baseline	Electricity	Baseline collected in three 2-week periods throughout study	Lightbulb would light up when use within 90% of peak from baseline

McCalley, L. T., and Midden, C. J. H. (2002). Energy conservation through product-integrated feedback: The roles of goal-setting and social orientation. Journal of Economic Psychology, 23, 589–603.	2002	4 groups (N = 100) 1. Feedback with no goal manipulation (N=25) 2. Feedback with a self-set goal (N=25) 3. Feedback with an experimentor assigned goal (N=25) 4. No feedback no goal (N=25)	100	4	single session lab study	Electricit y	Baseline trials at beginning of study	Washing machine control panel
Mountain, D. (2006). The Impact of Real-Time Feedback on Residential Electricity Consumption: The Hydro One Pilot. March 2006.	2006	2 groups (N=552): 1. Electronic Feedback (N=500) 2. Control (N=52)	552	2	18 mos baseline 12 mos intervention	Electricit y	18 months of baseline data prior to intervention	
Petersen, J. E, Shunturov, V., Janda, K., Platt, G., and Weinberger, K. (2005). Does providing dormitory residents with feedback on energy and water use lead to reduced consumption? Proceedings of Greening the Campus VI. Petersen, J.E., Shunturov, V., Janda, K., Platt, G., and Weinberger, K. (2007). Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives. *International Journal of Sustainability in Higher Education*, 8(1), 16-33.	2007	3 groups: 1. High resolution real-time data (2 dormitories) 2. Low resolution weekly data (16 dormitories) 3. 2 dorm floors received no feedback	dormitories	3	~5 weeks total: 3 weeks baseline 2 weeks intervention (a campuswide energy saving competition)	Electricit y and Water	3 weeks of baseline prior to intervention	Website
Sexton, R. J., Johnson, N. B., and Konakayama, A. (1987). Consumer response to continuous-display electricity-use monitors in a time-of-use pricing experiment. *Journal of Consumer Research* 14(1), 55-62.	1987	2 groups: (N = 218) 1. experimental group randomly chosen from all customers (N =68) 2. control group (N = 150)	218	2	2 years: 1 year baseline 1 year intervention	Electricit y	Previous year's consumption data	Digital display
Ueno, T., Inada, R., Osamu, S., Tsuji, K. Effectiveness of Displaying energy Consumption Data in Residential Houses: Analysis on how the Residents Respond. *Proc. ECEEE 2005*, 1289-1299. Ueno T., Sano, F., Saeki, O., Tsuji, K.. (2006). Effectiveness of an energy-consumption information system on energy savings in residential houses based on monitored data. *Applied Energy* 83, 166–183.	2005	2 Groups (N=19): 1. Control (N=9) 2. Electronic Feedback (N=10)	19	2	~9 mos	Electricit y and Gas		"Information Terminal" (PC)
Van Houwelingen, J.H. and Van Raaij, W. (1989). The Effect of Goal-Setting and Daily Electronic Feedback on In-Home Energy Use. *Journal of Consumer Research*, 16(1), 98-105.	1989	6 groups (N=285 after attrition) 1. The Indicator 2. Monthly external feedback 3. Self-monitoring 4. Conservation info only 5. Control group 1 6. Control group 2	285	6	3 years: 1 year baseline 1 year intervention 1 year followup	Natural gas	Previous year's consumption data	Digital display
Wood, G., Newborough, M. (2003). Dynamic Energy-Consumption Indicators for Domestic Appliances: Environment, Behavior and Design. *Energy and Buildings* 35, 821-841.	1999	4 groups (N=41): 1. Control (N=12) 2. Information packet (N=12) 3. Electronic feedback (N=10) 4. Packet + feedback (N=9)	41	4	~2.5 mos baseline 2 mos intervention	Electricit y (at electric stove)	~2.5 months of baseline data prior to intervention	Custom 5-line LCD display

Appendix B.
Survey Materials for Formative Water Study

This appendix contains screenshots from the nine pages of the online survey presented in Chapter 6. The right-hand column in each screenshot specifies whether an answer was required for each question.



1. IRB

Preview Reorder Copy Page Delete Page Edit Page Options

ID: 168 Add Note

Required

Soft-Required [?]

Skip Question Num.

Researcher Contact Information
Jon E. Froehlich
PhD Candidate
Computer Science and Engineering
jfroehli@cs.washington.edu

RESEARCHERS' STATEMENT
We are asking you to be in a research study. The purpose of this consent form is to give you the information you will need to help you decide whether to be in the study or not. Please read the form carefully. You may ask questions about the purpose of the research, the possible risks and benefits, your rights as a volunteer, and anything else about the research or this form that is not clear by emailing jfroehli@cs.washington.edu. After reading this form, you can decide if you want to be in the study or not. This process is called "informed consent." You can print a copy of this form for your records.

PURPOSE OF THE STUDY
We are studying how people think about energy, water, and gas usage in the home.

STUDY PROCEDURES
To participate in this study, you simply need to fill out the forthcoming online survey. Please try to answer each question carefully and honestly. At the end of the survey, we will ask you for your email address. You do not need to provide this information. Those respondents that do supply their email addresses will be entered in a raffle to win a $50 gift certificate to Amazon.com.

amazon.com $50

RISKS, STRESS, OR DISCOMFORT
We do not expect any risks, stresses, or discomforts as a result of this research.

BENEFITS OF THE STUDY
Although you may not directly benefit from this study, we hope that the findings of this study will help to develop new technology that will help the environment.

OTHER INFORMATION
Taking part in this study is voluntary. You can stop filling out the survey at any time. Information about you is anonymous. The information you provide is not linked to your name.

SUBJECT'S STATEMENT
This study has been explained to me. I volunteer to take part in this research. If I have questions later about the research, I can email one of the researchers listed above. If I have questions about my rights as a research subject, I can call the University of Washington Human Subjects Division at (206) 543-0098.

By clicking 'Yes' below, you consent to take part in this study. *

Yes

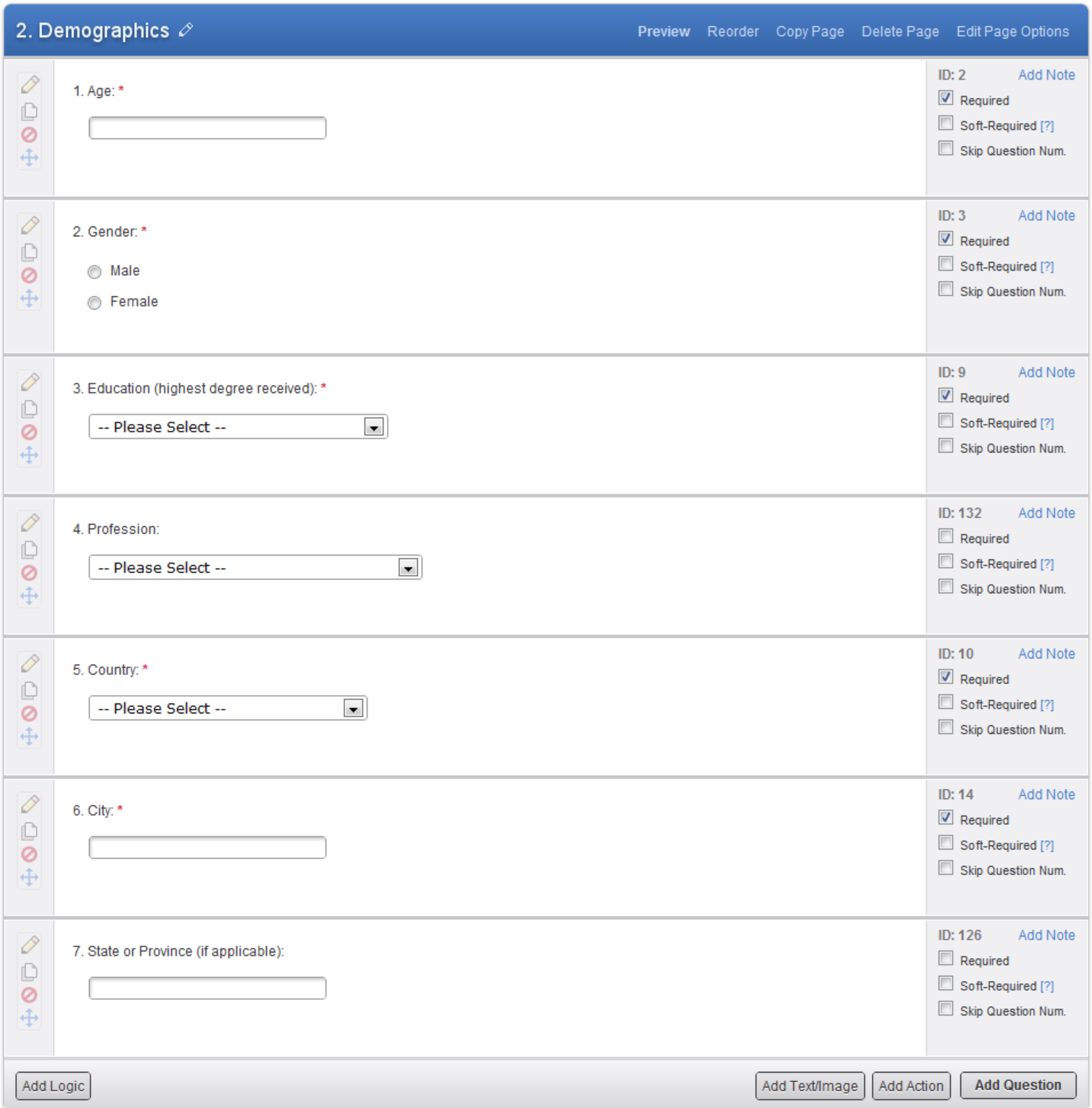
No

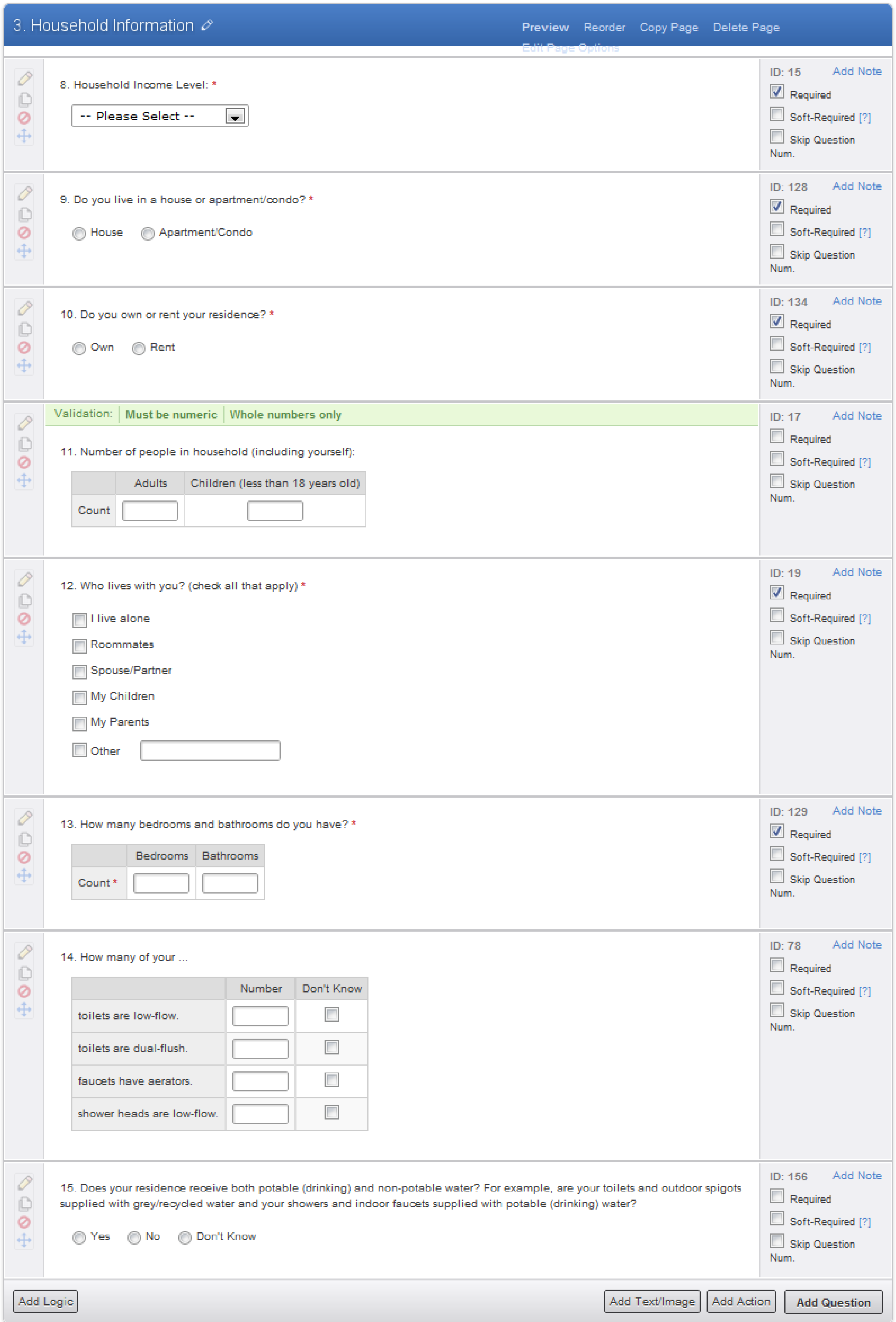
Add Logic | Add Text/Image | Add Action | Add Question

Page Logic — the following conditions will run when the page above gets submitted

New Page Logic Action:
IF: The answer to Question # is exactly equal to **No**

THEN: Disqualify and display:
In order to take this survey, you must say 'Yes' to the consent form. Thank you for your interest in our survey. We hope you have a great day! :)


2. Demographics
Preview
Reorder
Copy Page
Delete Page
Edit Page Options
1. Age: *
ID: 2
Add Note
Required
Soft-Required [?]
Skip Question Num.
2. Gender: *
Male
Female
ID: 3
Add Note
Required
Soft-Required [?]
Skip Question Num.
3. Education (highest degree received): *
-- Please Select --
ID: 9
Add Note
Required
Soft-Required [?]
Skip Question Num.
4. Profession:
-- Please Select --
ID: 132
Add Note
Required
Soft-Required [?]
Skip Question Num.
5. Country: *
-- Please Select --
ID: 10
Add Note
Required
Soft-Required [?]
Skip Question Num.
6. City: *
ID: 14
Add Note
Required
Soft-Required [?]
Skip Question Num.
7. State or Province (if applicable):
ID: 126
Add Note
Required
Soft-Required [?]
Skip Question Num.
Add Logic
Add Text/Image
Add Action
Add Question



3. Household Information

Preview Reorder Copy Page Delete Page

8. Household Income Level: *

-- Please Select --

ID: 15 Add Note
Required
Soft-Required [?]
Skip Question Num.

9. Do you live in a house or apartment/condo? *

House Apartment/Condo

ID: 128 Add Note
Required
Soft-Required [?]
Skip Question Num.

10. Do you own or rent your residence? *

Own Rent

ID: 134 Add Note
Required
Soft-Required [?]
Skip Question Num.

Validation: Must be numeric | Whole numbers only

11. Number of people in household (including yourself):

	Adults	Children (less than 18 years old)
Count		

ID: 17 Add Note
Required
Soft-Required [?]
Skip Question Num.

12. Who lives with you? (check all that apply) *

- I live alone
- Roommates
- Spouse/Partner
- My Children
- My Parents
- Other

ID: 19 Add Note
Required
Soft-Required [?]
Skip Question Num.

13. How many bedrooms and bathrooms do you have? *

	Bedrooms	Bathrooms
Count *		

ID: 129 Add Note
Required
Soft-Required [?]
Skip Question Num.

14. How many of your ...

	Number	Don't Know
toilets are low-flow.		
toilets are dual-flush.		
faucets have aerators.		
shower heads are low-flow.		

ID: 78 Add Note
Required
Soft-Required [?]
Skip Question Num.

15. Does your residence receive both potable (drinking) and non-potable water? For example, are your toilets and outdoor spigots supplied with grey/recycled water and your showers and indoor faucets supplied with potable (drinking) water?

Yes No Don't Know

ID: 156 Add Note
Required
Soft-Required [?]
Skip Question Num.

Add Logic Add Text/Image Add Action Add Question

4. Billing/Water Supplier

Preview Reorder Copy Page Delete Page

16. Which metric of consumption are you most comfortable with? *

- Gallons
- Liters

ID: 192 Add Note
Required
Soft-Required [?]
Skip Question Num.

17. What do you think about the price of water in your area? *

Very High-Cost	High-Cost	About Right	Low-Cost	Very Low-Cost	I Don't Know
○	○	○	○	○	○

ID: 27 Add Note
Required
Soft-Required [?]
Skip Question Num.

Question Logic: Show/hide trigger

18. Does your household pay for water? *

- Yes
- No, we do not receive a water bill because we live in an apartment/multi-family dwelling
- No, we do not receive a water bill because we are on well water.
- Don't know
- No, other reason

ID: 190 Add Note
Required
Soft-Required [?]
Skip Question Num.

Question Logic: Show/hide trigger

19. Who typically pays the water bill in your home? *

- Myself
- Spouse/Partner
- Roommate
- Parent
- Don't know
- Other

ID: 191 Add Note
Required
Soft-Required [?]
Skip Question Num.

20. About how much is your typical water bill per month? Please do not consult your bill, an online website or other outside sources for this information. We are interested in your perception of water cost. *

If you don't know, write-in "Don't Know". If amount is not in dollars, please specify currency type (e.g., euros, Canadian dollars).

ID: 28 Add Note
Required
Soft-Required [?]
Skip Question Num.

21. How much time do you spend looking at your water bill when it arrives? *

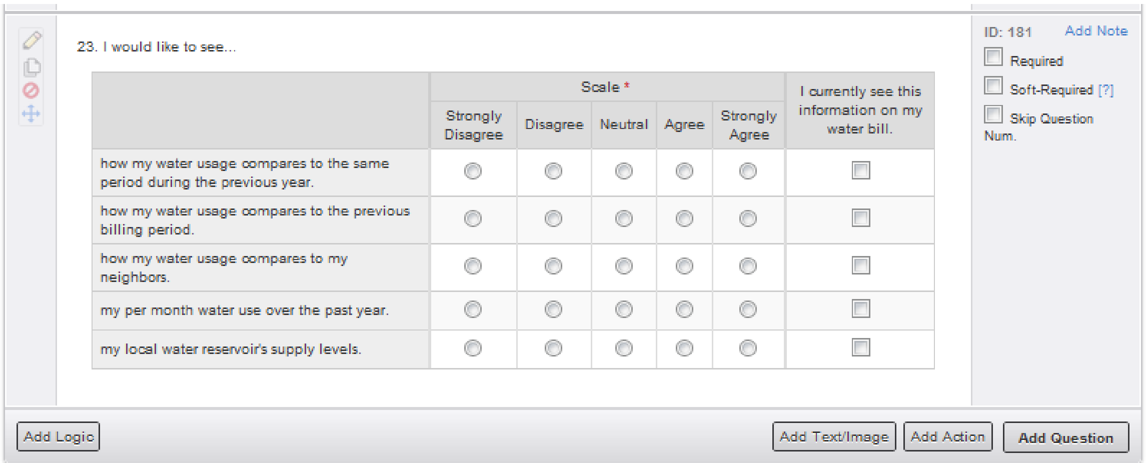
More than 10 minutes	5 to 10 minutes	1 to 5 minutes	Less than 1 minute	I don't look at it
○	○	○	○	○

ID: 30 Add Note
Required
Soft-Required [?]
Skip Question Num.

22. What information do you look at when you receive your water bill? Select all that apply.

- Overall water volume consumed
- Total due
- Overall cost of water used
- Cost of sewage
- Rate charge per unit of water
- Other

ID: 180 Add Note
Required
Soft-Required [?]
Skip Question Num.



ID: 181 Add Note

Required

Soft-Required [?]

Skip Question Num.

23. I would like to see…

	Scale *					I currently see this information on my water bill.
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	
how my water usage compares to the same period during the previous year.						
how my water usage compares to the previous billing period.						
how my water usage compares to my neighbors.						
my per month water use over the past year.						
my local water reservoir's supply levels.						

Add Logic

Add Text/Image

Add Action

Add Question

5. Water Usage Perceptions/Behaviors

Preview Reorder Copy Page Delete Page

Edit Page Options

Question Logic:
Hidden unless: (Question #16 contains any("Gallons") AND Question #19 contains any("Myself","Spouse/Partner","Roommate","Parent","Other"))

ID: 101 Add Note
Required
Soft-Required [?]
Skip Question Num.

24. Estimate how much you pay per gallon of water in your home. Please do not consult your bill, an online website or other outside sources for this information. We are interested in your perception of water cost.
If the amount is not in US dollars, please specify currency type in the box provided.

	Amount *	Currency	Confidence Level *		
			Very Confident	Somewhat Confident	Not At All Confident
Cost per gallon			◯	◯	◯

Question Logic:
Hidden unless: (Question #16 contains any("Liters") AND Question #19 contains any("Myself","Spouse/Partner","Roommate","Parent","Other"))

ID: 174 Add Note
Required
Soft-Required [?]
Skip Question Num.

25. Estimate how much you pay per liter of water in your home. Please do not consult your bill, an online website or other outside sources for this information. We are interested in your perception of water cost.
If the amount is not in US dollars, please specify currency type in the box provided.

	Amount *	Currency	Confidence Level *		
			Very Confident	Somewhat Confident	Not At All Confident
Cost per liter			◯	◯	◯

ID: 36 Add Note
☑ Required
Soft-Required [?]
Skip Question Num.

26. Who do you think uses the most water in your house? *

- ◯ I do
- ◯ My spouse/partner
- ◯ My child
- ◯ My parent
- ◯ My roommate

ID: 37 Add Note
Required
Soft-Required [?]
Skip Question Num.

27. Why do you think this person uses the most water?

Question Logic: Hidden unless: Question #19 contains any("Myself","Spouse/Partner","Roommate","Other")

ID: 38 Add Note
☑ Required
Soft-Required [?]
Skip Question Num.

28. The amount I spend on my water bill influences my water usage behaviors. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Applicable
◯	◯	◯	◯	◯	◯

Question Logic: Show/hide trigger

ID: 39 Add Note
☑ Required
Soft-Required [?]
Skip Question Num.

29. When you use water, do you try and limit how much you're using? *

Never	Seldom	About Half the Time	Usually	Always
◯	◯	◯	◯	◯

Question Logic: Show/hide trigger

30. Which of the following reasons do you consider important when limiting your water usage?

	Unimportant	Of Little Importance	Moderately Important	Important	Very Important
Cost of water	○	○	○	○	○
Cost of sewage	○	○	○	○	○
Environmental concerns	○	○	○	○	○
Current weather conditions (e.g., drought)	○	○	○	○	○
Requests to conserve by water supplier	○	○	○	○	○
Laws or city mandates	○	○	○	○	○
Other reason (specify below)	○	○	○	○	○

ID: 65 Add Note
☐ Required
☐ Soft-Required [?]
☐ Skip Question Num.

Please write in your response here if you responded "Other reason" above.

ID: 82 Add Note
☐ Required
☐ Soft-Required [?]
☑ Skip Question Num.

Validation: Min. answers = 3 *(if answered)*

This question type is non-interactive **here** (in the editor). Preview your survey to see it work properly.

31. Please rank the top THREE fixtures in terms of how much water they consume in general in an average month. The rankings are highest (most water) to lowest. It's alright if you don't know, just guess. *
Drag items from the left-hand list into the right-hand list to order them.

Drag items from the left-hand list into the right-hand list to order them.

- Low-flow Toilet
- Bathroom Faucet
- Standard Shower
- Refrigerator Water Dispenser
- Bath
- Low-flow Shower
- Kitchen Faucet
- Standard Toilet
- Bidet
- Laundry Machine
- Outdoor Hose Spigot / Lawn Irrigation System
- Dishwasher

ID: 91 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

32. I feel confident that I understand each of the following measurements and could explain their quantity/definition to a friend. *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Watts *	○	○	○	○	○
Kilowatt-Hours *	○	○	○	○	○
Gallons *	○	○	○	○	○
Gallons per Minute (gpm) *	○	○	○	○	○
Liters *	○	○	○	○	○
Liters per Minute (lpm) *	○	○	○	○	○
100 Cubic Feet (CCF) *	○	○	○	○	○

ID: 161 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

Add Logic | Add Text/Image | Add Action | Add Question

6. Water Usage Perceptions/Behavior Continued

Preview Reorder Copy Page Delete Page

Edit Page Options

33. Compared to other households with the same number of occupants, I think my household uses... *

- more than the average amount of water.
- an average amount of water.
- less than average amount of water.

ID: 43 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

34. I... *

	Not Applicable	Never	Rarely	Sometimes	Usually	Always
use my own bag when shopping. *	○	○	○	○	○	○
buy organic. *	○	○	○	○	○	○
try to limit the amount of water I use in my garden. *	○	○	○	○	○	○
use energy efficient light bulbs. *	○	○	○	○	○	○
wait until there's a full load for washing clothes/dishes. *	○	○	○	○	○	○
turn the tap/faucet off while brushing my teeth. *	○	○	○	○	○	○
turn the tap/faucet off when soaping up my face/hands. *	○	○	○	○	○	○
turn the tap/faucet off when washing dishes. *	○	○	○	○	○	○
recycle glass/newspaper/cans. *	○	○	○	○	○	○
use energy efficient appliances. *	○	○	○	○	○	○
reduce the number of baths/showers I take. *	○	○	○	○	○	○
reduce the hot water temperature in my hot water heater. *	○	○	○	○	○	○
purchase environmentally friendly detergents. *	○	○	○	○	○	○
buy bed linens made out of 100% recycled fiber. *	○	○	○	○	○	○
try to use yard products with Greensulgar-D. *	○	○	○	○	○	○

ID: 139 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

Question Logic: Show/hide trigger

35. Are there other measures that you could take to conserve water but have not? *

- Yes
- No

ID: 46 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

What measures are those?

ID: 47 Add Note
☐ Required
☐ Soft-Required [?]
☑ Skip Question Num.

Question Logic: | Hidden unless: **Question #16 contains any("Gallons")**

ID: 48 Add Note

☑ Required

☐ Soft-Required [?]

☐ Skip Question Num.

36. How much water do the following activities use? We are interested in your perception of these activities so please do not ask others or look online for the answer. *

	Gallons *	Confidence Level *		
		Confident	Somewhat confident	Not at all confident
Taking a bath		○	○	○
Taking a 10 minute shower with standard showerhead		○	○	○
Taking a 10 minute shower with low-flow showerhead		○	○	○
Using your dishwasher		○	○	○
Hand washing dishes		○	○	○
Leaving the tap on while brushing teeth (for one minute)		○	○	○
Flushing standard toilet		○	○	○
Flushing a low-flow toilet		○	○	○
Using a standard garden sprinkler for an hour		○	○	○

Question Logic: | Hidden unless: **Question #16 contains any("Liters")**

ID: 187 Add Note

☑ Required

☐ Soft-Required [?]

☐ Skip Question Num.

37. Copy of How much water do the following activities use? We are interested in your perception of these activities so please do not ask others or look online for the answer. *

	Liters *	Confidence Level *		
		Confident	Somewhat confident	Not at all confident
Taking a bath		○	○	○
Taking a 10 minute shower with standard showerhead		○	○	○
Taking a 10 minute shower with low-flow showerhead		○	○	○
Using your dishwasher		○	○	○
Hand washing dishes		○	○	○
Leaving the tap on while brushing teeth (for one minute)		○	○	○
Flushing standard toilet		○	○	○
Flushing a low-flow toilet		○	○	○
Using a standard garden sprinkler for an hour		○	○	○

Add Logic | Add Text/Image | Add Action | Add Question

7. Conservation Outlook

Preview Reorder Copy Page Delete Page

Edit Page Options

Page Options: Randomize all questions on this page

38. I am interested in conserving water in my home. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

ID: 53 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

39. I am concerned about global climate change. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

ID: 54 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

40. I believe that global climate change will affect water supplies. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

ID: 55 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

Question Logic: Show/hide trigger

41. I am concerned with the water supply in my area. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

ID: 56 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

Why are you concerned?

ID: 57 Add Note
☐ Required
☐ Soft-Required [?]
☑ Skip Question Num.

42. Everyone has the right to use natural resources as much as they want. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

ID: 135 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

43. My personal welfare isn't affected by environmental problems. *

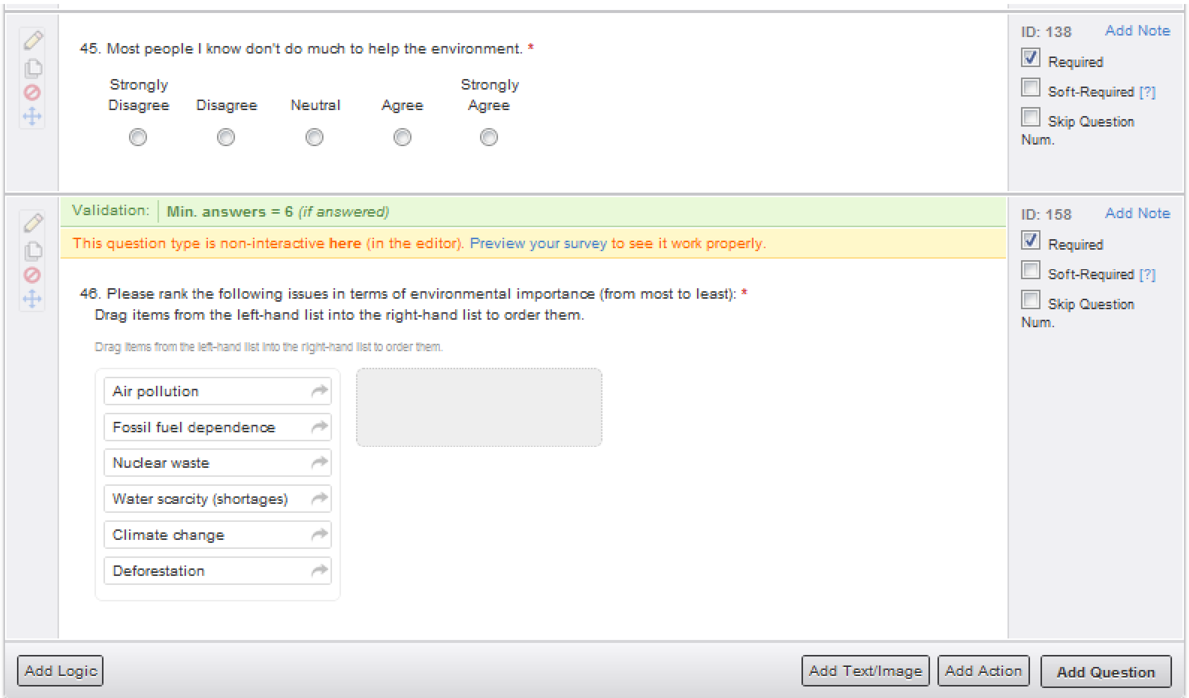
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

ID: 136 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.

44. Most of my neighbors and friends are environmentally friendly. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

ID: 137 Add Note
☑ Required
☐ Soft-Required [?]
☐ Skip Question Num.


45. Most people I know don't do much to help the environment. *
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree
ID: 138
Add Note
Required
Soft-Required [?]
Skip Question Num.
Validation:
Min. answers = 6 (if answered)
This question type is non-interactive here (in the editor). Preview your survey to see it work properly.
ID: 158
Add Note
Required
Soft-Required [?]
Skip Question Num.
46. Please rank the following issues in terms of environmental importance (from most to least): *
Drag items from the left-hand list into the right-hand list to order them.
Drag items from the left-hand list into the right-hand list to order them.
Air pollution
Fossil fuel dependence
Nuclear waste
Water scarcity (shortages)
Climate change
Deforestation
Add Logic
Add Text/Image
Add Action
Add Question

8. Email

Preview Reorder Copy Page Delete Page Edit Page Options

Validation: Email format expected

ID: 127 Add Note
Required
Soft-Required [?]
Skip Question Num.

47. Please provide us with your email adress.
Your email address will not be associated with the answers you submitted. It will be used to enter you into our drawing.

ID: 184 Add Note
Required
Soft-Required [?]
Skip Question Num.

48. Can we contact you with one (and only one) additional follow-up survey using the email address you provided? If yes, you will have another opportunity to earn a $50 Amazon gift certificate.

Yes

ID: 193 Add Note
Required
Soft-Required [?]
Skip Question Num.

49. Additional Comments (optional):

Add Logic Add Text/Image Add Action **Add Question**

Insert Page

9. Thank You!

Preview Reorder Results Chart Edit Page Options

ID: 1 Add Note

I really appreciate you taking the time to complete this survey. Your responses will be used to **inform the design of future water conservation programs** and will be incorporated into my Pł dissertation.

We have a follow-up survey to this one on the visual design of water usage feedback displays. really appreciate it if you could fill this out as well. Here's the link:

http://edu.surveygizmo.com/s3/602740/WaterUsageFeedbackInterfaces

Because it may take slightly longer to complete this survey (20-30 minutes), we are **doubling tl amount of the Amazon gift certificate draw from $50 to $100**.

All the best,

Jon E. Froehlich
PhD Candidate, Computer Science
University of Washington
jfroehli@uw.edu

Add Text/Image Add Action

Appendix C.
Pilot Testing of Water Usage Displays

The displays used in Chapter 9 were developed using an iterative process of design critiques and three pilot studies. Each pilot study involved semi-structured interviews with 15-20 participants recruited on a college campus. Interviews lasted 10-30 minutes and sought positive and negative feedback on multiple design ideas presented in sketch form or on an electronic display. This appendix describes the fixture icon and comparison pilot testing process.

Fixture Icons

We pilot tested several sets of fixture icons with 19 participants. The icon sets are shown in Figure C.1, with the final set used in our designs found at the bottom of the figure. Subjective feedback results from participants are shown in Table C.1.

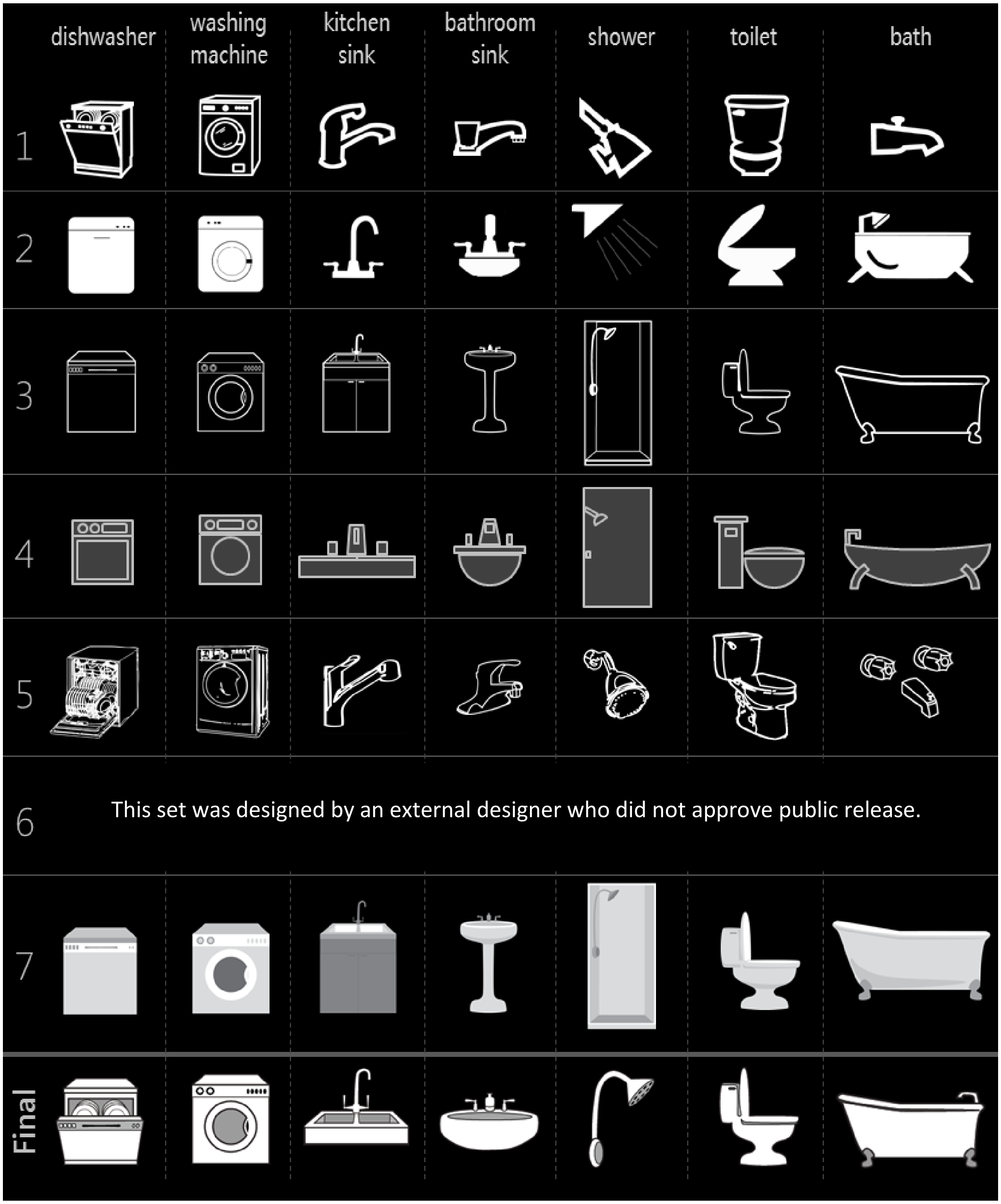


Figure C.1: The seven fixture icon sets used in pilot testing. The last row is the final, iterated icon set based on feedback from our pilot tests.

Design	Overall	Dishwasher	Laundry	Kitchen Sink	Bathroom Sink	Shower	Toilet	Bath	# Winning Categories
1	8	10	4	4	0	1	2	1	1
2	4	1	0	5	2	7	0	3	1
3	5	2	8	4	12	9	7	4	4
4	3	0	0	2	0	0	1	1	0
5	4	4	4	1	4	1	3	2	0
6	5	3	2	2	0	3	6	7	1
7	3	1	3	1	4	1	0	3	0

Table C.1: The results from pilot evaluation of the various fixture/appliance icons shown in Figure C.1 with 19 participants. Participants were first asked to select their favorite icon from each column and then their favorite icon set (row). Participants could select more than one option for both questions.

Comparison Strategies

Pilot Testing and Iterating on Visual Depictions of Comparison Data

Using the bar graph as our base design, we brainstormed approximately fifteen different ways of visualizing comparison data. In particular we focused on visualizing an *average value* in comparison to the *current value* for each bar (*e.g.,* rendering daily average data juxtaposed to the "so far today" data). The designs we ultimately pilot tested are shown in Figure C.2, along with a baseline that offers no comparison. These options can be differentiated along a number of different design decisions:

- What should carry more visual weight: the current value or the average value? In our case, we decided that the current usage amount was the primary data point and that the comparison data was complementary. Our designs reflected this decision. Design 6 is the only design in which both the current value and the average value are rendered with similar visual weight.
- Should overages be emphasized—in other words, should the design visually differentiate current usage data that has surpassed the average? Similarly, should the design indicate when a current value is getting close to the average? Four of our designs (1, 2, 5, and 7) visually indicated when a current value passed the average. The others made no visual distinction.
- How to visualize the average value itself? Should it be as a tick mark, as a line, as an additional bar? Each of these visual techniques has tradeoffs in visual noise, comprehensibility, and familiarity.
- Visualizing averages as gray backdrops ("back shadows"): Designs 1, 2, 3 and 5 dually encoded the average amount both with a tick, line or some other visual indication in addition to a subtle back shadow, which was the size and height of the value bar but faded to dark gray (and thus perceived to be in the background). Back shadows subtly allow the user to compare their current usage with typical (average) usage.

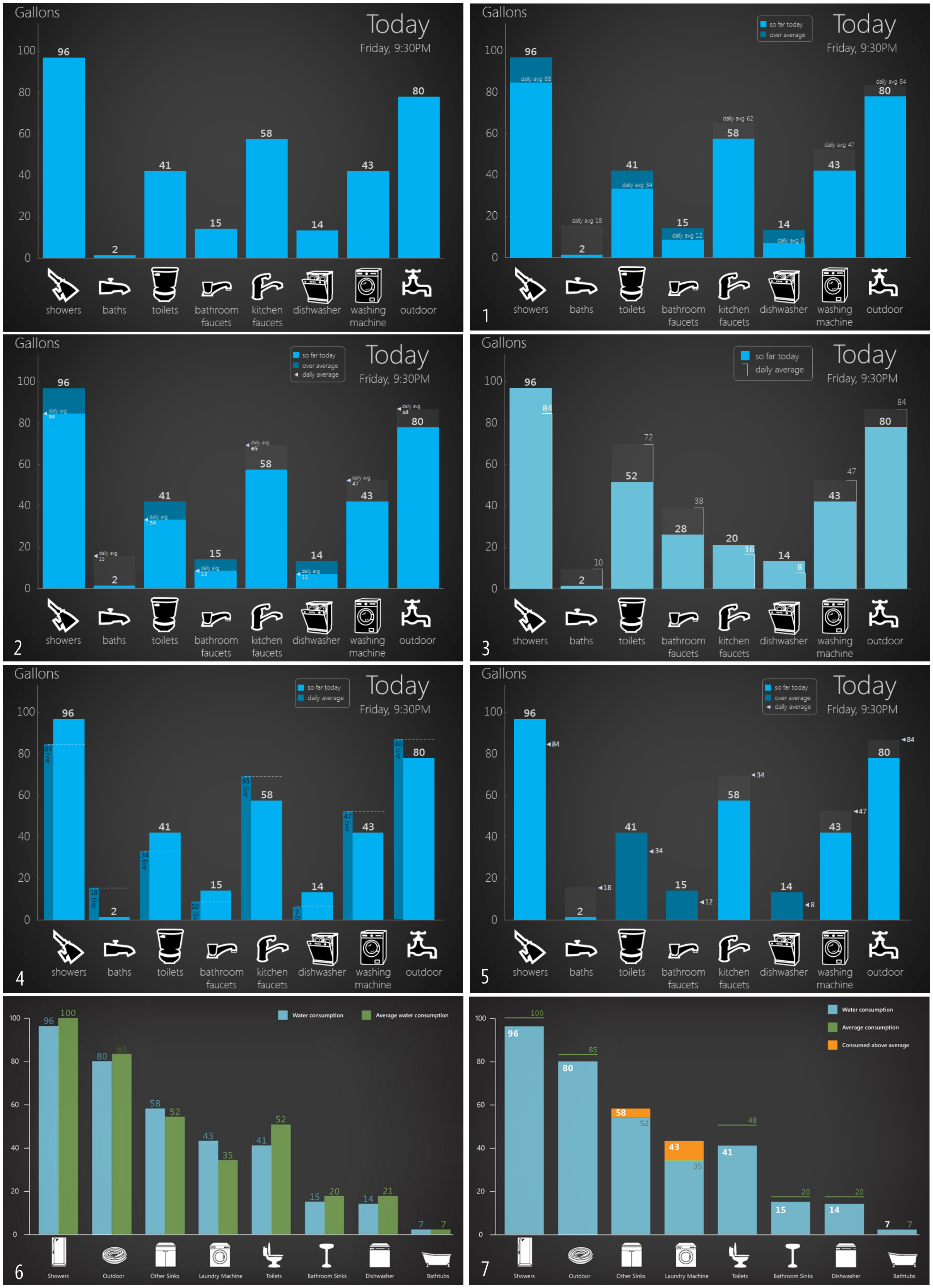


Figure C.2: The seven comparison designs used in pilot testing and the baseline (top-left) Each *comparison* design is numbered in bottom-left corner. The two-bar designs (4 and 6) received the most positive feedback.

Design	One Bar or Two	Backshadow	Visualization for Average Location	Visual Change When Average Passed	Most Favorite	Least Favorite
1	One	Yes	Text only	Yes	3	0
2	One	Yes	Triangle tick mark (inside bar)	Yes	0	1
3	One	Yes	Inverse hockey stick	No	0	3
4	Two	No	Bar plus line	No	9	6
5	One	Yes	Triangle tick mark (outside bar)	Yes	2	2
6	Two	No	Bar	No	3	2
7	One	No	Floating line	Yes	0	2

Table C.2: A description of the seven different visual designs (Figure C.2) for rendering comparison data along with the results from pilot testing. Seventeen participants were shown the designs and asked to vote for their favorite and least favorite.

We filtered the fifteen original comparison designs down to the seven shown in Figure C.2 based on an internal vote within the research group. The vote incorporated individual favorites as well as the objective to include a diverse range of approaches. We pilot tested these seven remaining designs with seventeen participants. Participants were approached randomly on the University of Washington campus while waiting for their food at a local taco bus. As a consequence, pilot participants were primarily students, faculty and staff. The designs were shown on a 1280x800 touchscreen laptop. These pilot tests were designed to be informal and semi-structured. Participants were rewarded with a small candy bar (or two) of their choice for participating.

We found that the two-bar designs (Designs 4 and 6), in general, were the most understandable and the most preferred. Unlike many of the other designs, the two-bar visualizations seemed familiar to our participants and, in this way, seemed more approachable and less confusing. One pilot participant remarked, "I like having two bars because it reminds me of what's in the newspapers" and another said, "I'm used to seeing it [data] in that way." Those who did not like the two-bar designs felt that it seemed like "too much information" and that it took away from reading and comparing the current value bars. A few participants mentioned not liking the sideways text in Design 4 and one observed that the "hanging line draws your attention more to what fixtures are *not* over the average rather than which fixtures are."

Participants who voted for the first design liked that the overages were immediately apparent by the darker blue and that each number was clearly labeled. The issue with this sort of design, however, is that a collision occurs when the average and current amount are close in value. We designed around this issue for pilot testing by specifically setting values apart so that these collisions did not occur but this issue would have to be solved for an actual deployment.

We found two main issues with the use of back shadows: (1) back shadows are reminiscent of progress bars in that the current value seems to fill along them—but progressing towards the average is not necessarily the intent of the design making it a somewhat malformed technique; and (2) if the current value passes the average, the back shadow is no longer visible. We found this to be confusing.

After reviewing this feedback, we determined that the best approach would be to utilize a two-bar design. These designs were the most liked amongst our participants and seemed well-understood. The primary criticism was that the second bar (for the average) was distracting. We attempted to minimize this by drawing the average bar smaller than the current value bar and coloring it with a darker blue tone. The final comparison design is shown in Figure C.3.

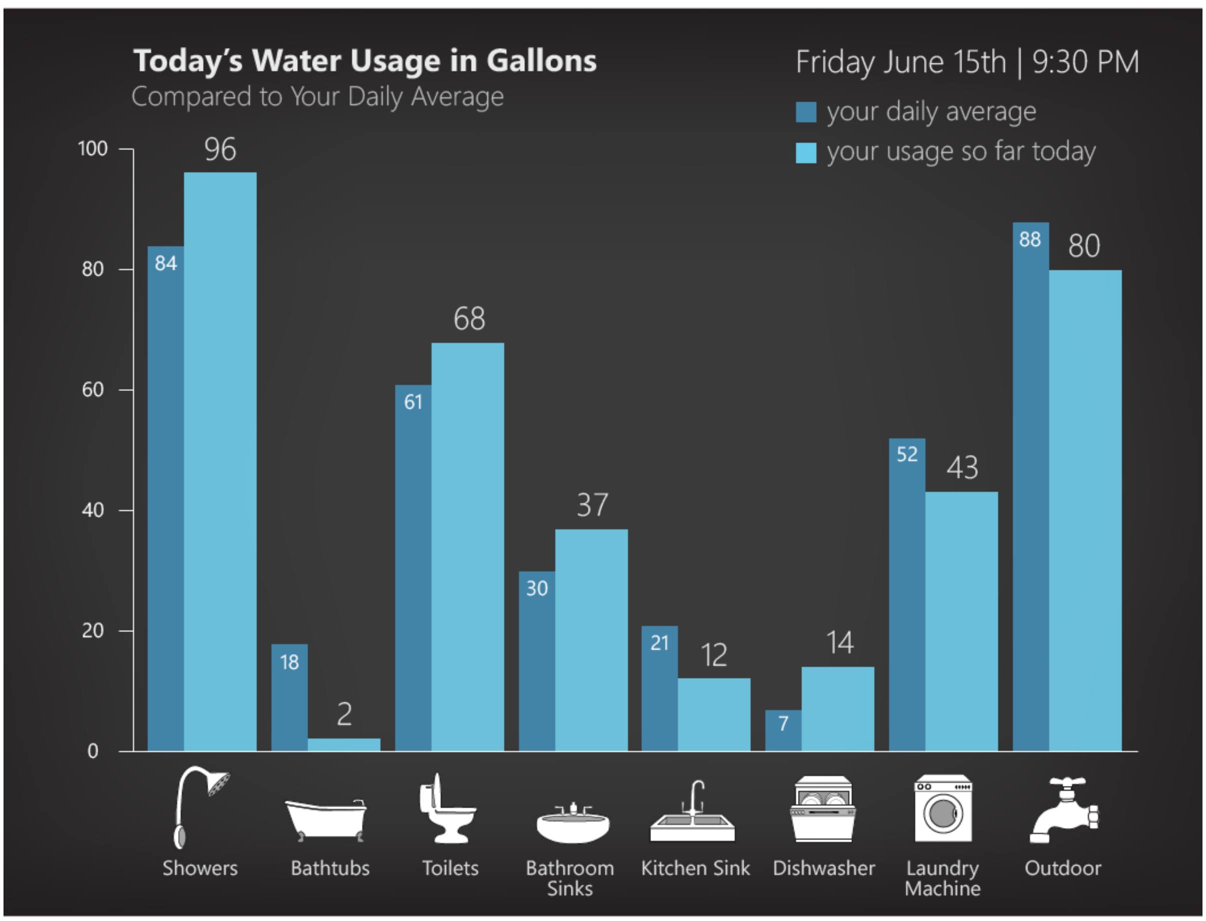


Figure C.3: The final comparison design after iteration based on feedback from pilot testing.

Appendix D.

Evolution of Water Display Design Probes

The final design probes described in Chapter 9 evolved through an iterative process including design critiques and pilot testing. This appendix provides samples of these evolving designs.

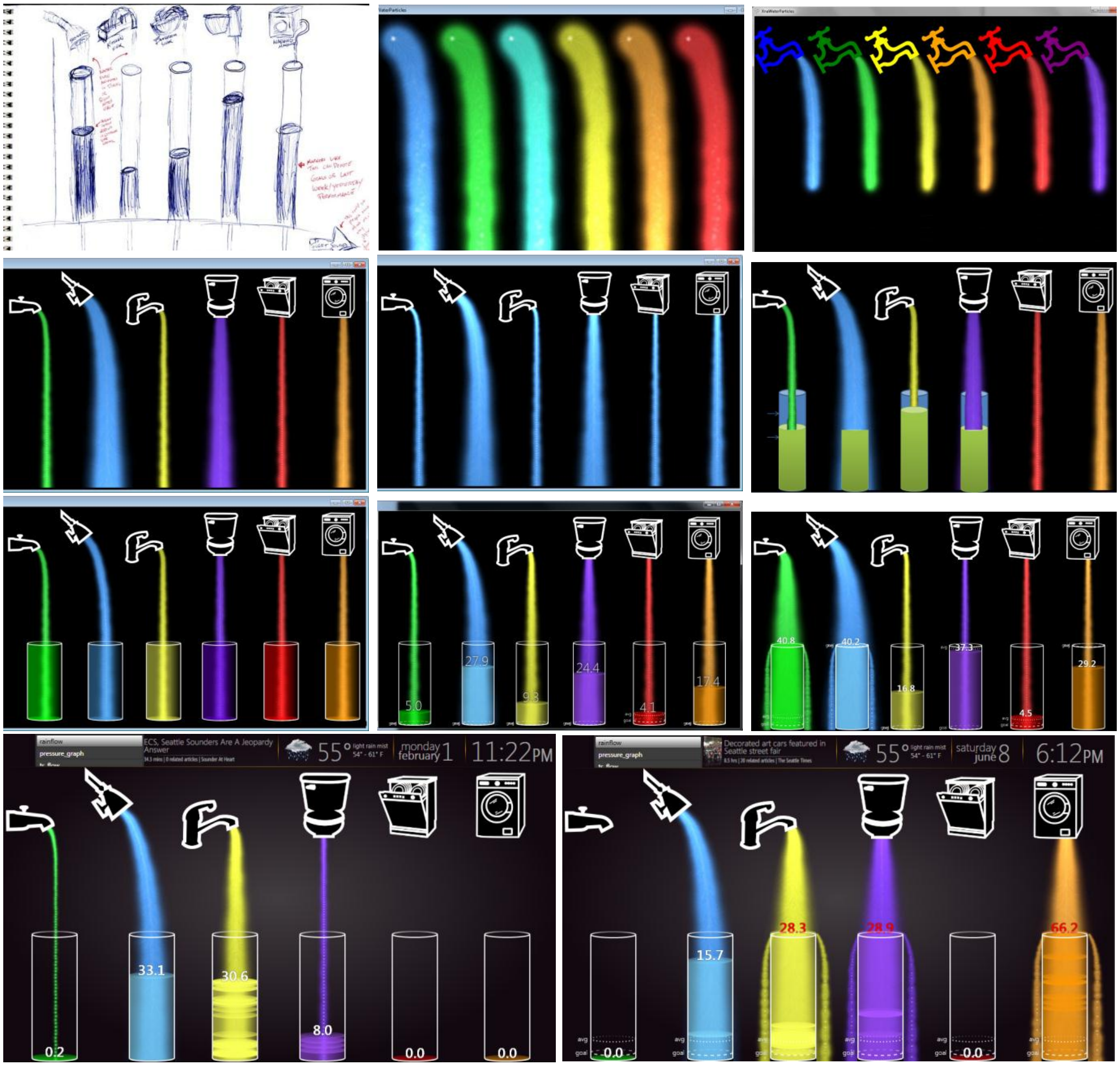


Figure D.1: The design evolution of the Rainflow visualization. The primary idea was to have water flow out of various fixtures upon use with a container filling according to the amount consumed. In this way, the containers themselves were really just stylized bar graphs. Later designs added tick marks to track historical averages and goals as well as a numerical label at the fill line showing the current amount used. One design variation had the containers overflow when the current volume used for any particular fixture exceeded the container size.

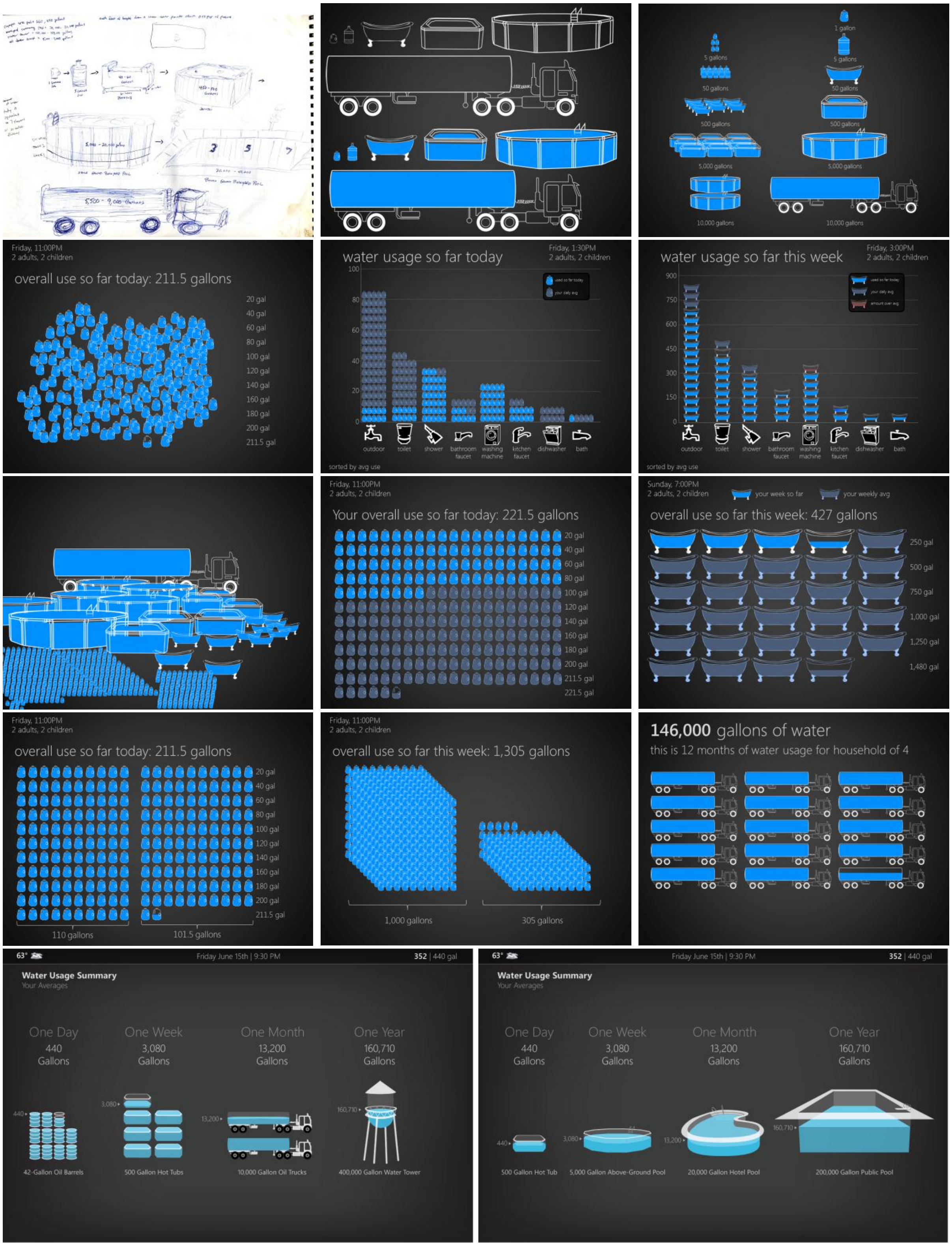


Figure D.2: The design evolution of Metaphorical Unit displays. Common objects used to convey water usage amounts include a 1-gallon jug, a 5-gallon jug, a 50 gallon bathtub, a 5,000 gallon above-ground pool, a 10,000 gallon oil truck, and a 400,000 water tower.

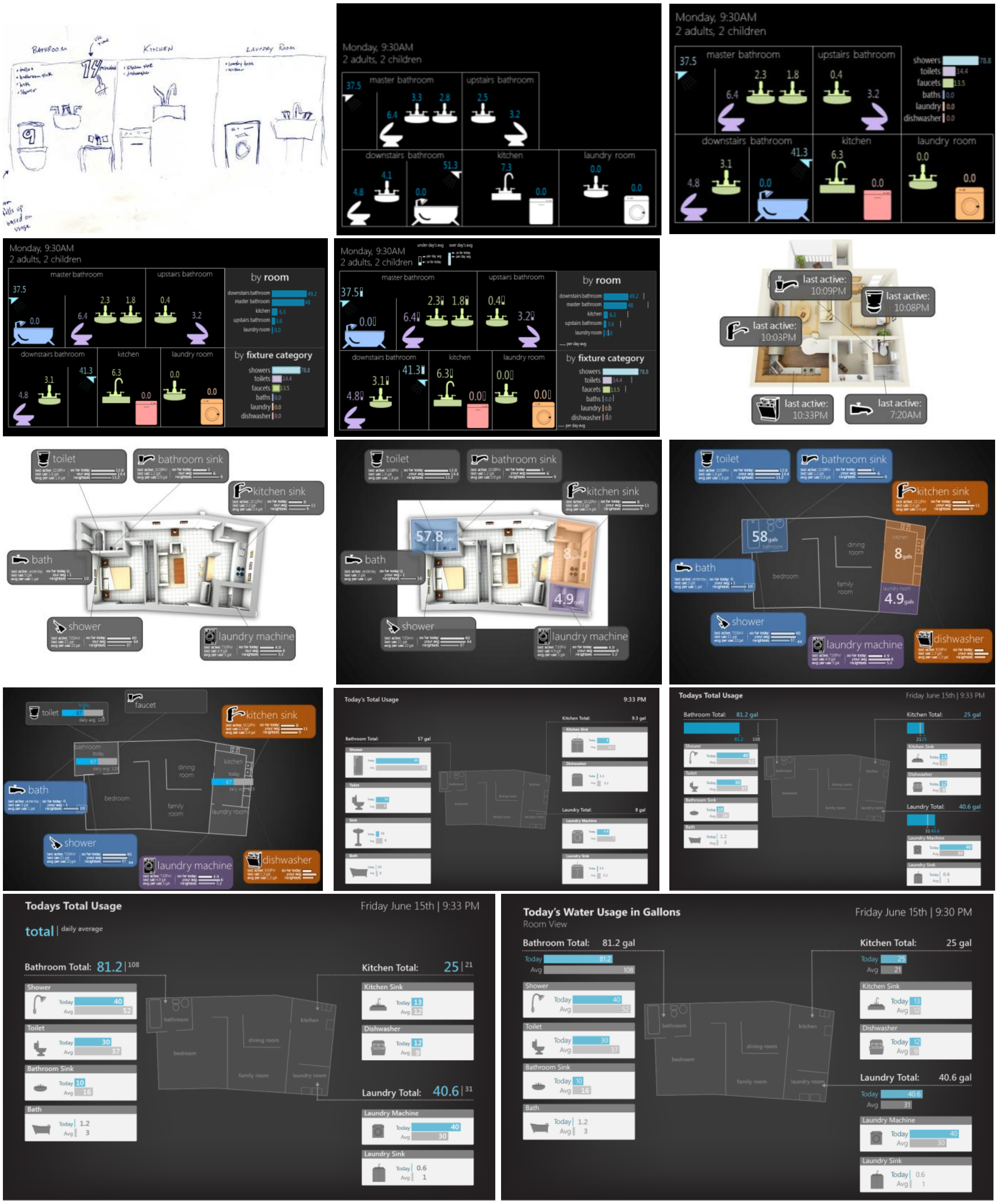


Figure D.3: The design evolution of a spatial or room-based layout of water usage information.

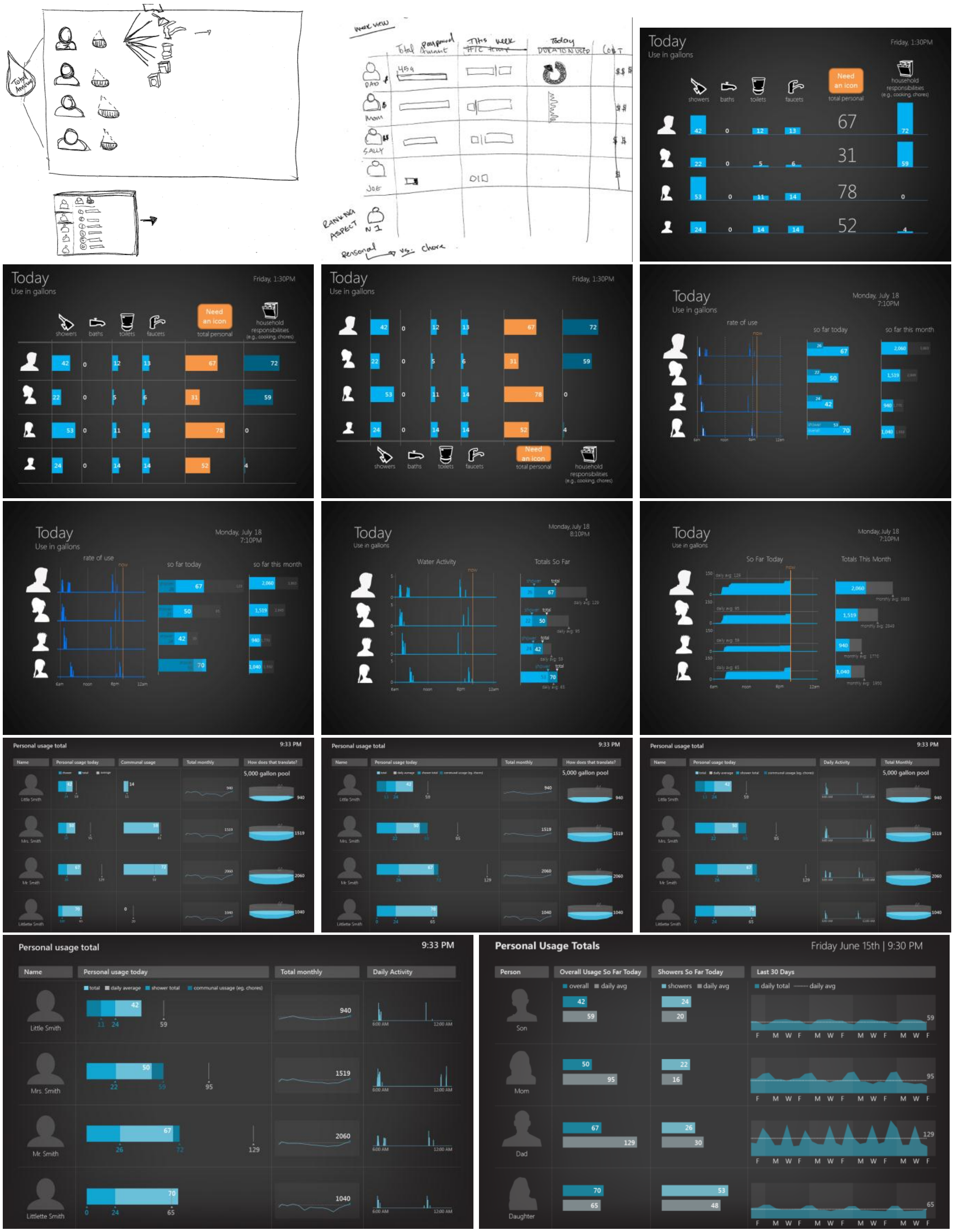


Figure D.4: The design evolution of the per-occupant displays

Figure D.5: The design evolution of the time-series displays.

Appendix E.
Survey Materials for Evaluation of Water Usage Displays

This appendix contains screenshots from the 19 pages of the online survey presented in Chapter 9.

Water Usage Displays Survey

Consent Form

0%

Hi, my name is Jon Froehlich and I'm a graduate student at the University of Washington. The survey you are about to take is for my PhD dissertation on water usage information systems. Your responses will help inform the design of future water conservation programs.

I appreciate you taking the time to fill out this survey,

Jon E. Froehlich
PhD Candidate
University of Washington

RESEARCHERS' STATEMENT
We are asking you to be in a research study. The purpose of this consent form is to give you the information you will need to help you decide whether to be in the study or not. Please read the form carefully. You may ask questions about the purpose of the research, the possible risks and benefits, your rights as a volunteer, and anything else about the research or this form that is not clear by emailing jfroehli@uw.edu. After reading this form, you can decide if you want to be in the study or not. This process is called "informed consent." You can print a copy of this form for your records.

PURPOSE OF THE STUDY
We are studying how computer displays (interfaces) can help inform people about their energy, water, and gas usage in the home.

STUDY PROCEDURES
To participate in this study, you simply need to fill out the forthcoming online survey. Please try to answer each question carefully and honestly. The survey should take between 20-35 minutes to complete. At the end of the survey, we will ask you for your email address. You do not need to provide this information. Those respondents that do supply their email addresses will be entered in a raffle to win a **$100 gift certificate** to Amazon.com. We will not use your email for any other purpose or give out you email address to anyone for any reason.

RISKS, STRESS, OR DISCOMFORT
We do not expect any risks, stresses, or discomforts as a result of this research.

BENEFITS OF THE STUDY
Although you may not directly benefit from this study, we hope that the findings of this study will help to develop new technology that will help the environment.

OTHER INFORMATION
Taking part in this study is voluntary. You can stop filling out the survey at any time. Information about you is anonymous. The information you provide is not linked to your name.

SUBJECT'S STATEMENT
This study has been explained to me. I volunteer to take part in this research. If I have questions later about the research, I can email one of the researchers listed above. If I have questions about my rights as a research subject, I can call the University of Washington Human Subjects Division at (206) 543-0098.

The survey should take between **20-35 minutes** to fill out. If you would like to go back to a previous page once you start the survey, please **do not hit the "back" button on your browser**. Instead, use the "back" button located at the bottom of each survey page.

By clicking 'Yes' below, you consent to take part in this study. *

- Yes
- No

Next

0%

Water Usage Displays Survey

Introduction

6%

Most people receive information on their water usage from a monthly or bi-monthly bill. We are working on a new type of system that can **immediately show people how much water they are using** at each fixture in their home. This information could be viewed, for example, on a mobile phone, on a laptop, a digital picture frame, or on an in-home touchscreen display.

In this survey, we'll explore different ways of visually displaying water usage information. Unless otherwise noted, each design is based on an average North American household of four people with two adults and two teenagers.

First, though, we need to ask some demographic questions.

Back Next

6%

Water Usage Displays Survey

Demographics

11%

Once you finish this brief list of demographic questions, we'll start showing you various water usage feedback displays.

1. Age: *

2. Gender: *

- Male
- Female

3. Education: *

-- Please Select --

4. Profession: *

-- Please Select --

5. Country: *

-- Please Select --

6. City: *

7. State or Province (if applicable):

8. Household income level: *

-- Please Select --

9. Number of people in household (including yourself): *

	Adults	Children (less than 18 years old)
Count *		

10. How many bedrooms and bathrooms does your home/apartment have? *

	Bedrooms	Bathrooms
Count *		

11. Do you live in a house or apartment/condo? *

- House
- Apartment/Condo

12. Do you own or rent your residence? *

- Own
- Rent

13. Does your household pay for water? *

- Yes
- No, we do not receive a water bill because we live in an apartment/multi-family dwelling
- No, we do not receive a water bill because we are on well water.
- Don't know
- No, other reason

14. I am interested in conserving water in my home. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

15. I am concerned about global climate change. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

16. I consider myself a "green" or "eco-friendly" person. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Back Next

11%

Water Usage Displays Survey

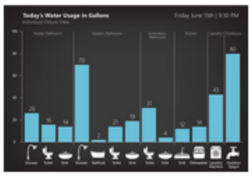
Data Grouping Intro

17%

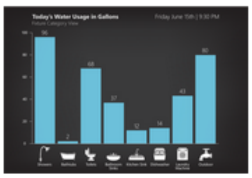
We have created three different examples of how **water usage information can be displayed**. Each example shows the same amount of water usage but groups the information differently.

On the next few pages, we will show each of the displays again (but one at a time) in random order and ask questions about them.

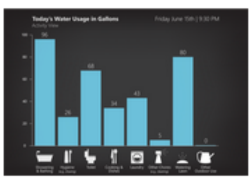
First, though, **please mouse over each of the thumbnails** to compare the information presented in the different designs. This mouse-over interaction will be used throughout the survey so it's useful to familiarize yourself with it now.



(a) Water usage by *individual fixture*.



(b) Water usage by *fixture type*.



(c) Water usage by *activity*.

Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

As you answer questions on the subsequent pages, remember that all of the displays shown in this survey **update immediately when water is used** in the home. Also, note that the water usage information in these displays is based on real water data for a North American home with two adults and two teenagers. For consistency, water usage is in gallons and the date and time is Friday, June 15th at 9:30PM across all displays.

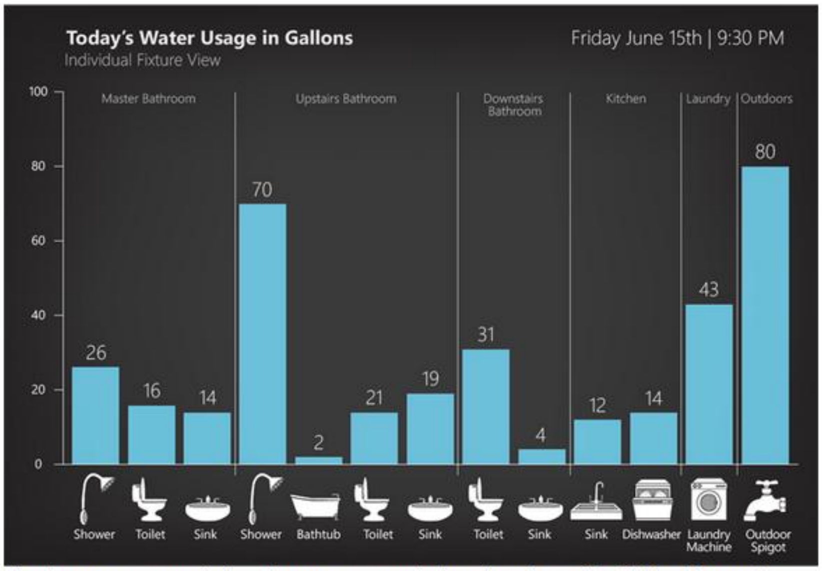
Back Next

17%

Water Usage Displays Survey

Fixture Level View

22%



The above water usage display shows water usage broken down by **each individual fixture** (e.g., master bathroom shower, upstairs bathroom toilet).

17. I find the individual fixture view display... *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Overwhelming/Confusing *	○	○	○	○	○
Informative/Useful *	○	○	○	○	○
Thought-provoking *	○	○	○	○	○
Attractive *	○	○	○	○	○
Easy to understand *	○	○	○	○	○

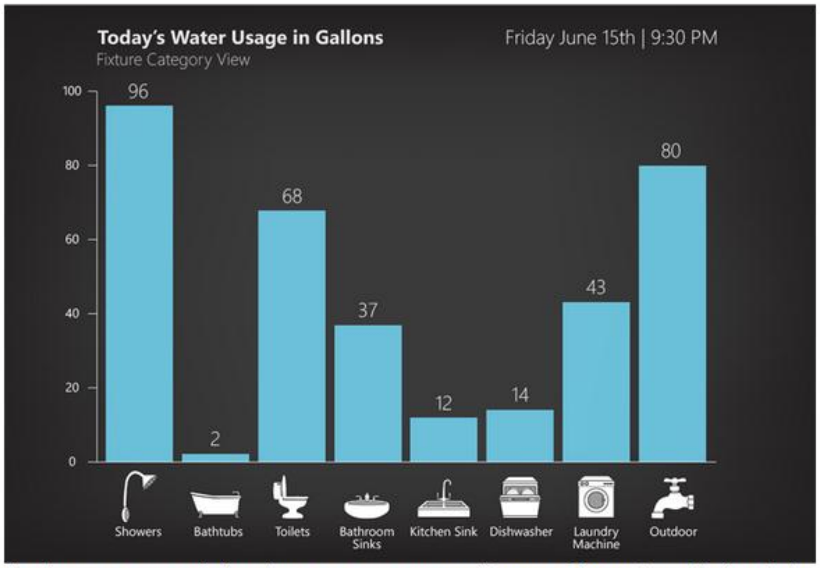
Back Next

22%

Water Usage Displays Survey

Fixture Category View

28%



The above water usage display shows water usage grouped by **type of fixture** (e.g., all toilets in the home are combined, all showers are combined, etc.).

18. I find the fixture category display... *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Attractive *	○	○	○	○	○
Thought-provoking *	○	○	○	○	○
Overwhelming/Confusing *	○	○	○	○	○
Informative/Useful *	○	○	○	○	○
Easy to understand *	○	○	○	○	○

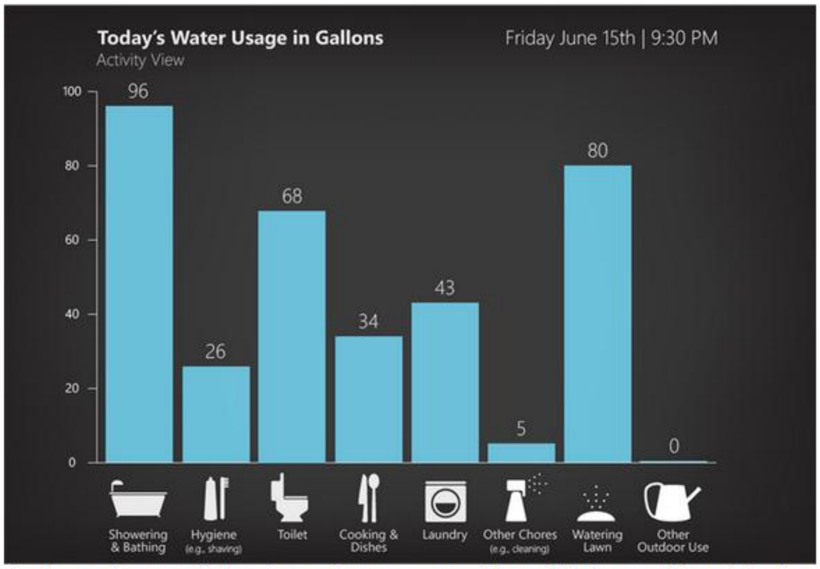
Back Next

28%

Water Usage Displays Survey

Activity View

33%



The above water usage display shows water usage **grouped by activity** (e.g., cooking and cleaning, lawn watering, personal hygiene).

19. I find the activity-based display... *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Informative/Useful *					
Overwhelming/Confusing *					
Attractive *					
Thought-provoking *					
Easy to understand *					

Back Next

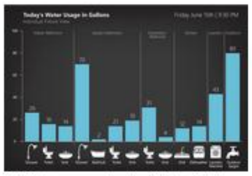
33%

Water Usage Displays Survey

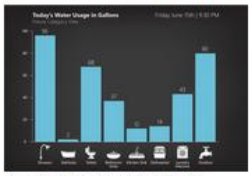
Data Grouping Preference

39%

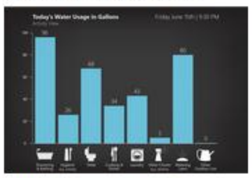
Here are the three data grouping displays shown together again for your convenience. Scroll down to view the question on this page.



(a) Water usage by *individual fixture*.



(b) Water usage by *fixture type*.

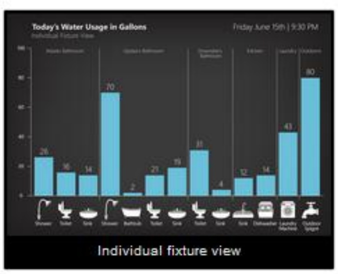


(c) Water usage by *activity*.

Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

20. Of these three displays, which do you think would be most useful in helping you to conserve water? *

Click on the display itself to make your selection. Note that the order of the displays below may be different from the order you saw them in on the previous pages.



21. Why? (optional)

Back Next

39%

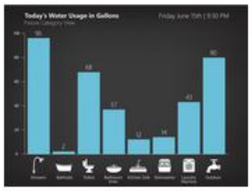
Water Usage Displays Survey

Hot and Cold Breakdown

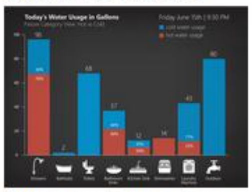
44%

We are also interested in whether people want **information on hot water usage vs. cold water usage**. Display (a) treats all water usage the same (whether hot or cold), while display (b) breaks down water usage by hot water and cold water amounts.

Like before, please mouse over the thumbnails on the left below to see enlarged versions of the display so that you can easily compare the two designs.



(a) Water usage by *fixture type*.

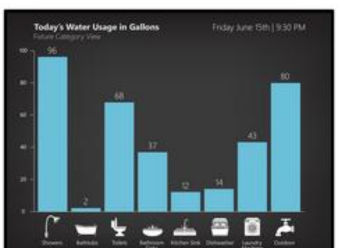


(b) Water usage by fixture type with *hot and cold breakdown*.

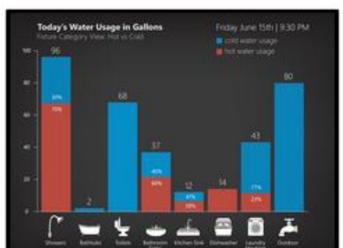
Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

22. Which display do you prefer? *

Click on the image below to make your selection.



Overall water usage by fixture type



Hot and cold water usage for each type of fixture

I would prefer to have both displays and be able to switch between them

All of the above

23. Why? (optional)

24. In general, I am interested in seeing how much hot water I use in comparison to cold water. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Back Next

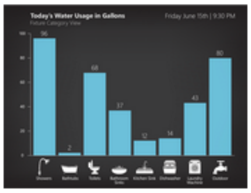
44%

Water Usage Displays Survey

Time Window to Display

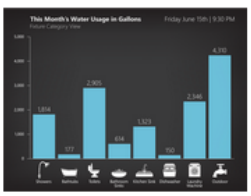
50%

This question is about **what time window of data** to display about water usage: (a) by day, (b) by week, or (c) by month.



(a) Water usage *so far today.*

(b) Water usage *so far this week.*



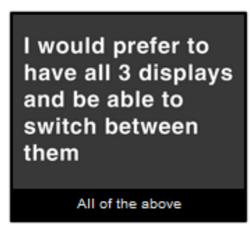
(c) Water usage *so far this month.*

Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

Remember that all of the displays shown in this survey (including the three above) **update immediately when water is used** in the home.

25. If you were trying to conserve water in your home, which display do you think would be most helpful? *

Click on an image below to make your selection.



26. Why? (optional)

Back Next

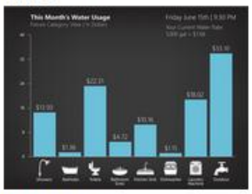
Water Usage Displays Survey

Measurement Unit

56%

Here, we are exploring three different ways of displaying consumption over the course of a month: (a) by gallons; (b) by cost of water; and (c) by both gallons and cost of water. Note that the cost of water in these graphs is based on billing rates in the city of Seattle, WA.

(a) By *gallons*.



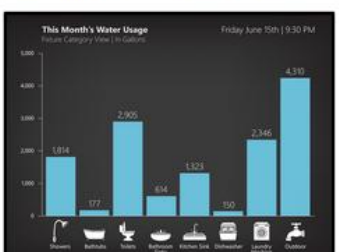
(b) By *cost of water*.

(c) By *gallons and cost* of water used.

Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

27. If you were trying to conserve water in your home, which display do you think would be most helpful? *

Click on an image below to make your selection.



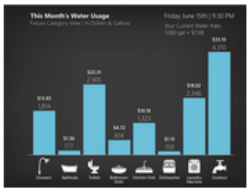
By gallons

By cost of water

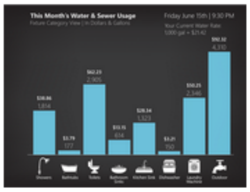
By gallons and cost of water

28. Why? (optional)

In addition to charging for water consumed, many water utilities charge for the cost of disposal (sewage). In Seattle, for example, the cost of sewage is $13.74 per 1,000 gallons of water used.



(a) By *gallons and cost of water.*



(b) By *gallons and cost of water* plus the *cost of sewage.*

Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

29. I would want the cost of sewage included in the displays that present cost information. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

30. Why? (optional)

Back Next

56%

Water Usage Displays Survey

Comparing Usage

61%

Finally, for the last set of questions in this part of the survey, we are interested in exploring displays that allow you to **compare** your current water usage **to your past** water usage, **to a goal** and/or **to other households' water usage**. We'll briefly ask about each in turn.

Display (a) below shows water usage so far today while display (b) adds comparative information in the form of your average daily usage.

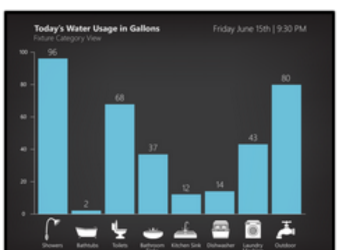
(a) Water usage by fixture type.

(b) Water usage by fixture type *compared to your average daily use.*

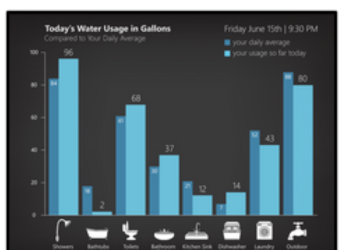
Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

31. Which display do you prefer? *

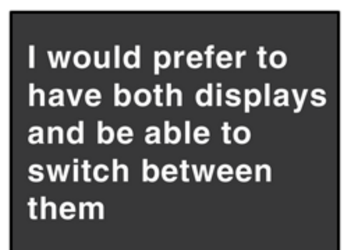
Click on the image below to make your selection.



Water usage so far today by fixture type



With comparison to your daily average



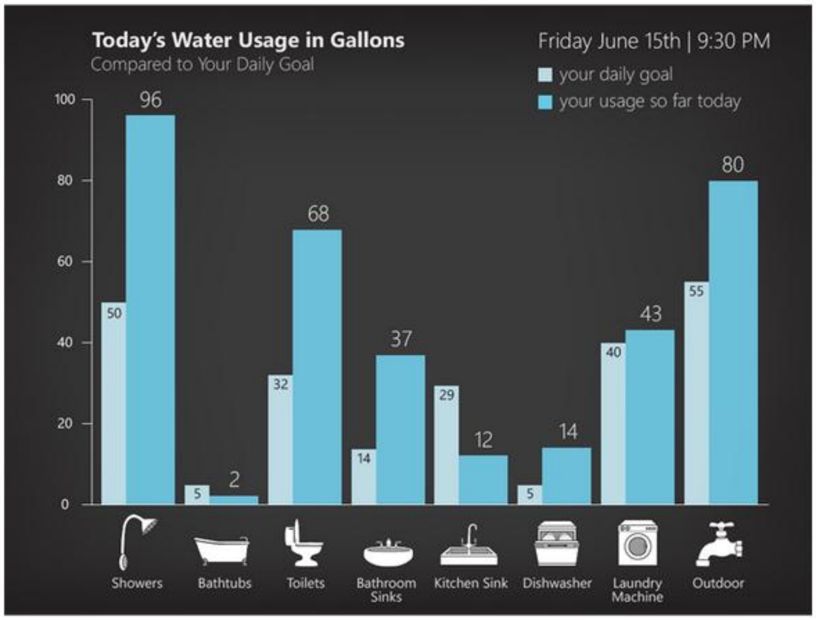
All of the above

32. Why? (optional)

33. In general, I am interested in comparing my current water usage to my past water usage. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
◎	◎	◎	◎	◎

The second type of comparison we are exploring is **comparing your water usage to a goal**. For example, this display shows your water usage so far today compared to a goal.



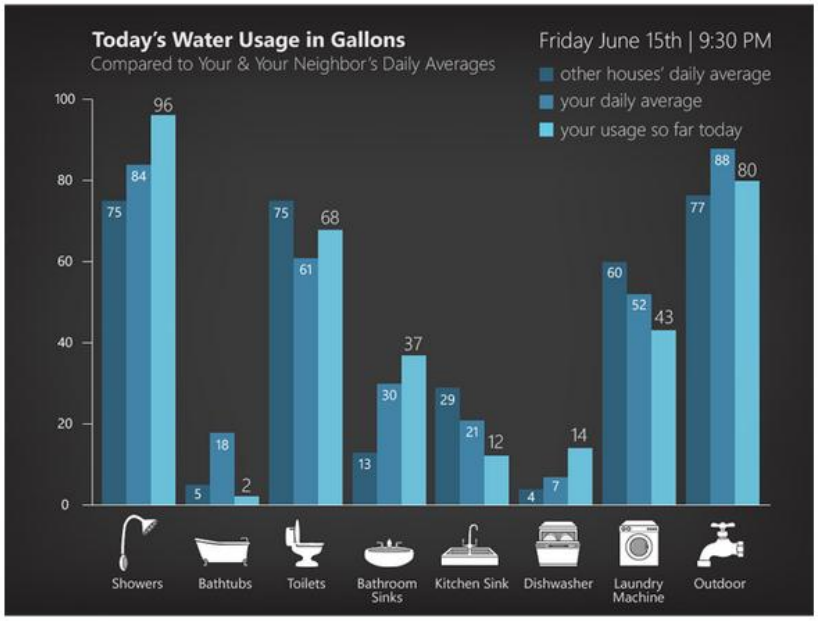
34. I would be interested in having the goal: *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Manually set by a member (or members) of the household *	◎	◎	◎	◎	◎
Automatically set by the display system to be 5% less than my daily average *	◎	◎	◎	◎	◎
Automatically set by the display system to the water usage amounts of my most water efficient neighbors *	◎	◎	◎	◎	◎
Automatically set by my water supplier (e.g., a public utility) *	◎	◎	◎	◎	◎
Automatically set by my local government *	◎	◎	◎	◎	◎

35. In general, I am interested in comparing my current water usage to a goal. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
◎	◎	◎	◎	◎

We are also exploring displays that allow you to compare your water usage with other households. For example, this display shows your water usage so far today, your daily average, and **the daily average of other households** (the definition of "other households" is explored below).



36. I would be interested in comparing my household's usage with: *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The average of other households that are geographically close to my house (e.g., my neighbors) *	◯	◯	◯	◯	◯
The average of other households that are demographically similar to my house (e.g., houses of similar size with the same number of occupants) *	◯	◯	◯	◯	◯
The average of other households that are conservative with water (i.e., water efficient households) *	◯	◯	◯	◯	◯
Households of family or friends that I choose *	◯	◯	◯	◯	◯
The average of other households in cities across my country *	◯	◯	◯	◯	◯
The average of other households in cities across the world *	◯	◯	◯	◯	◯

37. I would feel comfortable sharing my water usage data in order to enable these sorts of comparisons. The information would be completely anonymous (i.e., your household could not be identified from the data). *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
◯	◯	◯	◯	◯

38. In general, I am interested in comparing my current water usage to other households. *

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
◯	◯	◯	◯	◯

Back Next

61%

Water Usage Displays Survey

Design Themes Intro

67%

For the second and final part of this survey, we will be showing you **three different visual design themes** around water usage: (a) a time-based view; (b) a room-based view; (c) and a per-occupant view.

On the next page, we will show each of the displays again in random order and ask questions about them.

As usual, **please mouse over each of the thumbnails** to compare the information presented in the different designs.

(a) Time-based view.

(b) Room-based view.

(c) Per-occupant view.

Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

As before, remember that all of these displays **update instantly (once a second)** and therefore can immediately show new water usage information when a fixture or appliance is used.

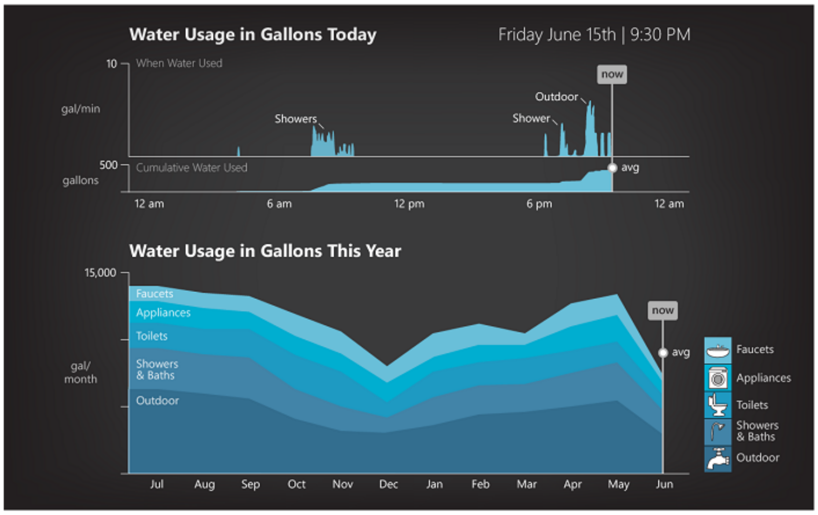
Back Next

67%

Water Usage Displays Survey

Time-based View

72%



This display shows water usage broken down by time. The top half shows water usage for the current day while the bottom half shows water usage for the past 12 months.

39. What type of fixture accounted for the greatest spike (jump) in water usage today? *

-- Please Select --

40. What complete month in the past used the least amount of water? Note that the current date in the display is June 15th, 2011. *

-- Please Select --

41. I find the time-based view… *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Attractive *	○	○	○	○	○
Overwhelming/Confusing *	○	○	○	○	○
Informative/Useful *	○	○	○	○	○
Easy to understand *	○	○	○	○	○
Thought-provoking *	○	○	○	○	○

42. Who do you think this display would appeal to in your home? *

Please check all that apply.

- ☐ Me
- ☐ My spouse/partner
- ☐ My roommate
- ☐ My sibling
- ☐ My parent
- ☐ My child
- ☐ Other
- ☐ No one

43. Why? (required) *

44. I would want to look at this display: *

More than once a day	Once a day	A few times a week	Weekly	Monthly	Never
○	○	○	○	○	○

45. Additional comments (optional):

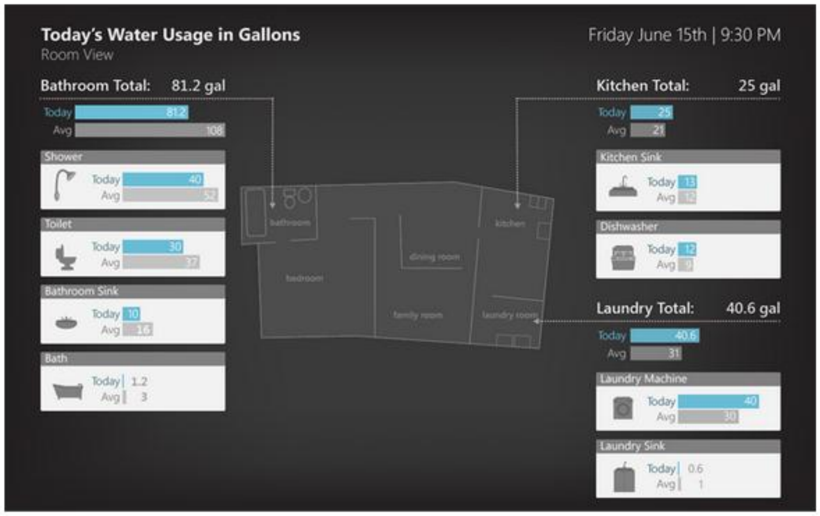
Back Next

72%

Water Usage Displays Survey

Room-based View

78%



This display shows water usage broken down by room. The current amount of water used so far today along with your daily average is visible for each room and each fixture.

46. Which room used the most water today? *

- ◯ Kitchen ◯ Bathroom ◯ Laundry ◯ I don't know

47. Which fixture, on average, uses the most water in this home? *

-- Please Select --

48. I find the room-based view… *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Overwhelming/Confusing *	◯	◯	◯	◯	◯
Thought-provoking *	◯	◯	◯	◯	◯
Easy to understand *	◯	◯	◯	◯	◯
Informative/Useful *	◯	◯	◯	◯	◯
Attractive *	◯	◯	◯	◯	◯

49. Who do you think this display would appeal to in your home? *

Please check all that apply.

- ☐ Me
- ☐ My spouse/partner
- ☐ My roommate
- ☐ My sibling
- ☐ My parent
- ☐ My child
- ☐ Other
- ☐ No one

50. Why? (required) *

51. I would want to look at this display: *

More than once a day	Once a day	A few times a week	Weekly	Monthly	Never
○	○	○	○	○	○

52. Additional comments (optional):

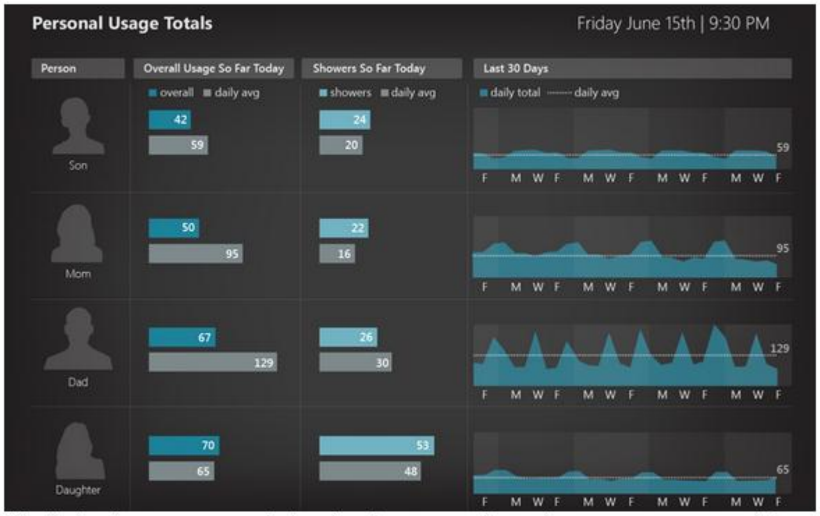
Back Next

78%

Water Usage Displays Survey

Per-occupant View

83%



This display shows water usage broken down by occupant. For each occupant, you can see their overall usage so far today, their shower usage so far today, and their water usage over the last 30 days as well as daily averages for each.

53. On average, which person in this home uses the most water? *

- Daughter
- Mom
- Dad
- Son
- I don't know

54. Who used the most water showering today? *

- Dad
- Mom
- Daughter
- Son
- I don't know

55. I find the per-occupant view... *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Easy to understand *	○	○	○	○	○
Thought-provoking *	○	○	○	○	○
Overwhelming/Confusing *	○	○	○	○	○
Attractive *	○	○	○	○	○
Informative/Useful *	○	○	○	○	○

56. Who do you think this display would appeal to in your home? *

Please check all that apply.

- Me
- My spouse/partner
- My roommate
- My sibling
- My parent
- My child
- Other
- No one

57. Why? (required) *

58. I would want to look at this display: *

More than once a day	Once a day	A few times a week	Weekly	Monthly	Never
○	○	○	○	○	○

59. Additional comments (optional):

Back Next

83%

Water Usage Displays Survey

Comparing the Visualizations

89%

Finally, here we're going to compare the various designs that you've seen. This is the final page of questions.

(a) Bar-graph view.

(b) Time-based view.

(c) Room-based view.

(d) Per-occupant view.

Move your mouse cursor over the image thumbnails on the left to see enlarged versions here.

60. Which display is the most… *

	(a) Bar-graph view	(b) Time-series view	(c) Room-based view	(d) Per-occupant view
Thought-provoking *				
Easy to understand *				
Overwhelming/Confusing *				
Attractive *				
Informative/Useful *				

61. Overall, which display is your favorite? *

Click on an image to make your selection.

62. Why? (required): *

63. Are there any other things that you would like to see in a water usage display that we did not include? If so, what? (optional)

Back Next

89%

Water Usage Displays Survey

Email

94%

64. Please provide us with your email address.

Your email address will not be associated with the answers you submitted. It will be used to enter you into our drawing.

65. Additional comments (optional):

Back Submit

94%

Water Usage Displays Survey

Thank You!

100%

I really appreciate you taking the time to complete this survey. Your responses will be used to **inform the design of future water conservation programs** and will be incorporated into my PhD dissertation. If you would like to learn more about my PhD research on water sensing and feedback, please visit my university webpage.

I hope you enjoyed the survey and maybe even learned something new. It would be very helpful if you could **forward the survey link** on to your friends and family members (if each person forwarded this survey to one other person it would double the number of respondents!).

Here's the link to use:
http://edu.surveygizmo.com/s3/602740/WaterUsageInterfaces

All the best,

Jon E. Froehlich
PhD Candidate, Computer Science
University of Washington
jfroehli@uw.edu

PS If you haven't taken our first survey on water usage practices, please take it here. It's another chance to help out and to be entered in another drawing for an Amazon gift certificate.

100%

Appendix F.
Water Display Interview Questions for Individual Members of Household

Each adult household member who participated in the interviews discussed in Chapters 6 and 9 completed the following short survey at the beginning of the interview session.

Instructions to participant: This survey is for each adult member of your household. Your responses will be protected by an anonymous id. We *will not look at your responses* until we get back to our research lab.

1. Age: ______________

2. Gender:

- ☐ Male
- ☐ Female

3. Education Level:

- ☐ 12th grade or less
- ☐ Graduated high school or equivalent
- ☐ Some college, no degree
- ☐ Associate's degree
- ☐ Bachelor's degree
- ☐ Post-graduate degree

4. Profession:

- ☐ Accounting / Finance / Banking
- ☐ News / Information

- ☐ Administration / Clerical / Reception
- ☐ Advertisement / PR
- ☐ Architecture / Design
- ☐ Arts/Leisure / Entertainment
- ☐ Beauty / Fashion
- ☐ Buying / Purchasing
- ☐ Construction
- ☐ Consulting
- ☐ Customer Service
- ☐ Distribution
- ☐ Education
- ☐ Health Care (Physical & Mental)
- ☐ Human resources management
- ☐ Management (Senior / Corporate)
- ☐ Operations / Logistics
- ☐ Planning (Meeting, Events, etc.)
- ☐ Production
- ☐ Real Estate
- ☐ Research
- ☐ Restaurant / Food service
- ☐ Sales / Marketing
- ☐ Science / Technology / Programming
- ☐ Social service
- ☐ Student
- ☐ Other____________________________
- ☐ N/A - Unemployed / Retired / Homemaker

5. I am interested in conserving water in my home.

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

6. I am concerned about global climate change.

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

7. I believe that global climate change will affect water supplies.

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

8. I consider myself a "green" or "eco-friendly" person.

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

9. Everyone has the right to use natural resources as much as they want.

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

10. Most of my friends and family would be considered "green" or "eco-friendly."

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

11. I am concerned with the availability of public supply water in my area.

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

12. I am concerned with the quality of public supply water in my area.

○ Strongly Disagree ○ Disagree ○ Agree ○ Agree ○ Strongly Agree

Appendix G.
Water Display Interview Questions for Entire Household

In addition to the Individual Survey in Appendix D, each household that was interviewed for Chapters 6 and 9 completed the following household-level survey.

Instructions to participants. This survey is for each household. Your responses will be protected by an anonymous id. We *will not look at your responses* until we get back to our research lab.

1. What is the approximate square footage of your residence: ___________________

2. How many bedrooms does your residence have? ______________________

3. How many bathrooms does your residence have?______________________

4. Number of adults (18 or older) in your residence:________________________

5. Number of children (less than 18) in your residence: ______________________

   5b. Please list the ages of your children:

   _________ _________ _________ _________ _________

6. Do you live in a house or apartment/condo? ○ House ○ Apartment/Condo

7. Do you own or rent your residence? ○ Own ○ Rent

8. Does your household pay for water?

   ☐ Yes
   ☐ No, we do not receive a water bill because we live in an apartment/multi-family dwelling
   ☐ No, we do not receive a water bill because we are on well water
   ☐ Don't know
   ☐ No, other reason: ____

Appendix H.
Water Display Interview Protocol

Household interviews conducted for Chapters 6 and 9 were based on the following interview questions and protocol. Green text denotes instructions to the interviewers.

Introduction

[Start timing! Should be at 65 minutes when ready to walk around house] We are going to interview each of you about your water usage activities and attitudes in the home as well as ask you about some water usage feedback designs that we've created. The interview is broken down into three parts:

1. The first part of the interview asks **background questions** about how you use water in the home and how you think about water

2. The second part of the interview asks about **various water usage feedback mockup designs** that we've created.

3. Finally, in the third part of the interview, we will walk around your home a bit and talk about **how the display might fit into various rooms**.

Part 1 – Background Questions about Water Attitudes/Knowledge

Water Use Practices and Perceptions In The Home

Main goals: (1) Get people comfortable answering questions and creating a rapport with you. (2) Household water usage practices and perceptions of water. (3) Differences in water use / perception across home occupants.

4. Do you know where your water comes from? Do you ever think about where your water goes after you use it? Do you know where it goes?

5. Which fixture or appliance do you think uses the most water in your home? Why?

6. How do different people in the family use water?

7. Who do you think uses the most water in the home? Why is that?

8. Do you ever think about how much water your family uses? If yes, what do you think when you think about it?

[Interviewees need not provide answers that relate to conservation here—we are interested in all aspects of water use. Potentially probe this if interviewees only provide conservation related answers (*e.g.,* how about issues outside of saving water?)]

9. [Sense of ownership around space in the home] Do you have multiple bathrooms? Do some people tend to use one over the others? Can you explain how that works and why?

10. Compared to other households with the same number of occupants as yours, do you think your house uses less, the same or more water than average? Why?

Water Conservation Knowledge and Practices

[Main goal: determine perspectives and know-how around water conservation in the home and tease out differences in water conservation practices and attitudes across home occupants]

11. When you use water do you try to limit how much you're using? How and why? [for each member of the household, including kids]

12. Are there other opportunities to conserve water in your home? What would that entail?

13. Have you ever heard of a low-flow fixtures such as low-flow showerhead or toilets? Do you know if you have any low flow fixtures in your home? Who installed them and why?

Billing and Payment Practices

[Main goal: determine relationship between cost and water in the household: if rate structures are understood, if price influences behavior; and who, in the household is in charge (just one person or more)]

14. About how much is your water bill per month? About how much does one gallon of water cost you?

15. Can you tell me a little bit about how the Seattle water rate structure works?

16. Does the amount of money you spend on water influence your usage? Why or why not?

17. Who looks at and pays the water bill?

18. About how much time do you spend looking at the bill when it arrives? What do you look at? Why?

Part 2 – Focus on the Eco-Feedback Display

Now, we're going to transition to the second part of this interview. Ordinarily, most people receive information on their water usage from a monthly or bi-monthly bill [show slide]. We are working on new technology that can immediately show people how much water they are using at each fixture in their home [hit enter to show next 3 displays].

Today, we're going to be focusing primarily on designs that could be shown on a laptop or on an in-home touch screen display [hold up framed touchscreen and show slide]

These displays can show water usage even for individual fixtures.

Grouping the Data

[The main point here is to introduce people to the eco-feedback displays.]

The first set of displays are bar graphs of water consumption using three different data groupings: by fixture category, by individual fixture and by water usage activity. You can see the thumbnails here. Now, we're going to show you each of these bar graphs enlarged to full screen and we'd like your initial reaction to each.

[for each display]

19. What do you think about the kind of information shown in this display? [potential prompts if necessary: Something you'd like to see for your own home? Do you think the information would be useful to you? If so, how?]

[once all three displays have been shown, ask…]

20. Which is your favorite and why?

Introduction of Designs We're Still Experimenting With

We would like to get some feedback on these early ideas. For example:

• What you like / don't like about them.

• What you think is attractive.

• What might be confusing.

• What you think might be useful about each one to conserve water.

• Who in your family might like each one and why.

[transcriber: make sure to note everyone's initial reactions both verbal and non-verbal]

[introduce each of the six quickly, then return to the first one and go through them slowly to discuss.]

a. **Time series**: these displays show water usage broken down by time

b. **Comparison**: these displays allow for comparison either within the household or to other households

c. **Rainflow**: this display is similar to the bar graph displays you've seen in the past but utilize containers in place of bars that fill up based on water usage. It is also animated.

d. **Measurement**: these displays allow for different uses of measurement units

e. **Aquatic Eco-system**: the amount of water you use in your home and where you use it changes the eco-system in the aquarium. [try not to refer to this as a game, let game emerge from their description]

f. **Per-occupant**: breaks down water usage by person in the home.

[for each of the six displays, ask the question below—remember this is supposed to be brief]

21.What are your initial thoughts of this display? Does this kind of breakdown seem like something your family would like to have? Why or why not?

[After each of the six designs (plus bar graph views) have been shown…

Show all the displays again and ask them to choose 2-3 that they would most like to have on a display in their home and would be able to switch between. Tell them the adults that they don't have to agree with each other.]

22. Why do you think the set you selected covers your family's needs or interests? Why did you choose these particular designs?

23. Beyond conservation, what do you think these displays might be useful for? [possible answers might include: I would be able to see if my kids are up in the morning; I could check to make sure that our lawn watering system is working properly; I could tell if we have leaks, etc.]

24. What do you think might motivate different members of your family to look at displays like this? To conserve water?

Per-occupant View

[Come back to per-occupant display to specifically target some questions about competition and privacy.]

25. What do you think this display would reveal about people in your home? [Possible probes: What about the scenario about telling when people are home? What about how long washed hands or didn't wash hands?]

26. [Privacy] Sometimes people find the idea of showing each household member's use because they like the extra details, it provides accountability. Other people, on the other hand, feel like it's too intrusive. How do you think the members of your family would feel about a display like this?

27. [Competition] What do you think about using competition to motivate water conservation? Why?

Part 3 - Placement in home

Now, we're going to transition to the third and final part of the interview. We would like you to think about two or three places where you might put this display in your home. We'd like to walk around with you and actually place the display in a location of your choosing.

[Walk around with them and the framed touchscreen with a design loaded as they show you these places. Have the household members themselves choose one of the designs to have up on the frame as you walk around the house. Note taker should right down which display was selected! For each of the locations ask the following question]

28. What do you think the pros/cons are of putting the display in this location?

29. How does the display fit into this room? Why? [For either positive or negative, try to get them to elaborate on why.]

30. How often do you think you'd look at the display here?

31. Who can/can't see the display if you put it here? Do you think that's good/bad?

Favorite Location for Display

32. Of the locations we've looked at for the display, which is your favorite?

33. [If they decide everyone needs to access to it, ask why? If they decide some people don't, ask why not?]

34. What do the kids think?

Quad Displays

[bring back the quad display of the various ways of water usage feedback]

35. Which display might be best for your home in helping you conserve water?

Amount of Most Recent Water Bill

36. Do you have a recent water bill? Can we see it? Would you mind if we wrote down the amount you used over the past year as well as how much you've spent?

Interview Questions for Children

a. How old are you?

b. Do you ever think about where your water comes from and where it goes after it goes down the drain?

c. What activity do you think you do that uses the most water?

d. Do you ever try and limit how much water you are using? Why or why not?

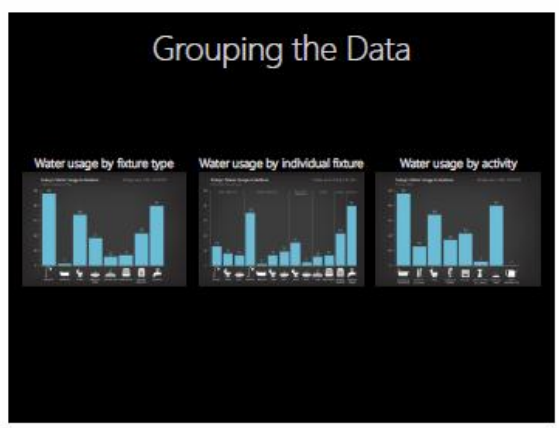
Wrap-up

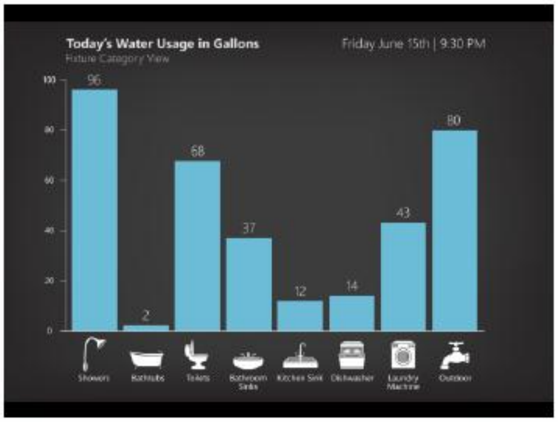
[Thank the family. Give them the payment and ask an adult to sign the receipt sheet.]

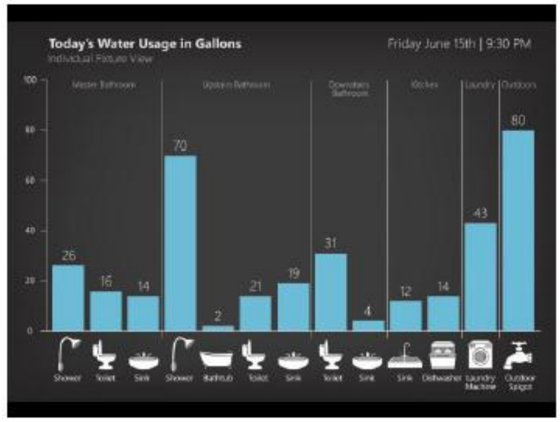
Appendix I.
Water Displays Evaluated in Household Interviews

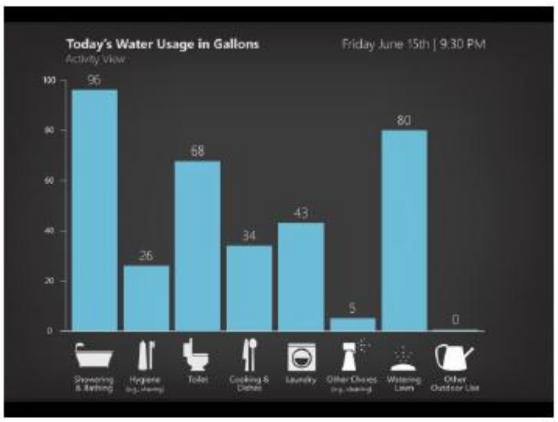
The following set of slides were shown to participants during the household interviews described in Chapters 6 and 9.

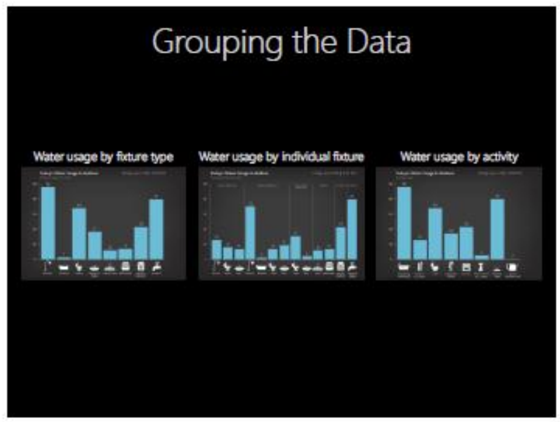
Water Usage
Feedback Interviews




Today's Water Usage in Gallons
Friday June 15th | 9:30 PM
Fixture Category View
96
2
68
37
12
14
43
80
Showers
Bathtubs
Toilets
Bathroom Sinks
Kitchen Sink
Dishwasher
Laundry Machine
Outdoor

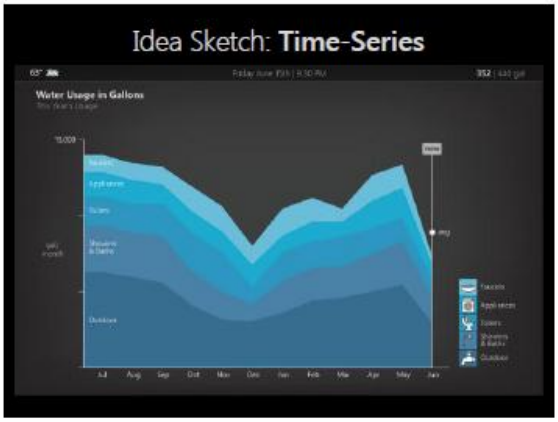

Today's Water Usage in Gallons
Friday June 15th | 9:30 PM
Laundry
26
16
14
70
2
21
19
31
4
12
14
43
80
Shower
Toilet
Sink
Shower
Bathtub
Toilet
Sink
Toilet
Sink
Sink
Dishwasher
Laundry Machine
Outdoor Spigot


Today's Water Usage in Gallons
Friday June 15th | 9:30 PM
Activity View
96
26
68
34
43
5
80
0
Showering & Bathing
Hygiene
Toilet
Cooking & Dishes
Laundry
Other Chores
Watering Lawn
Other Outdoor Use

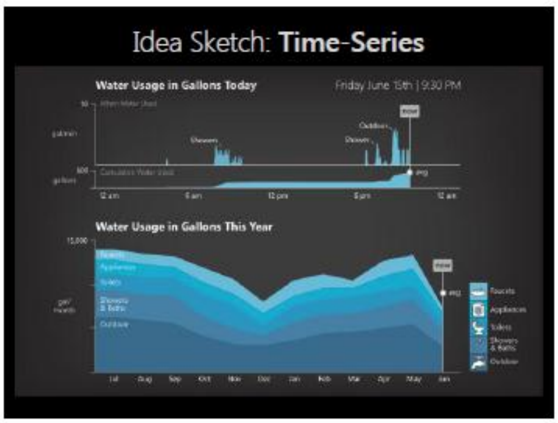

Grouping the Data
Water usage by fixture type
Water usage by individual fixture
Water usage by activity


Idea Sketches
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant


Idea Sketches
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant

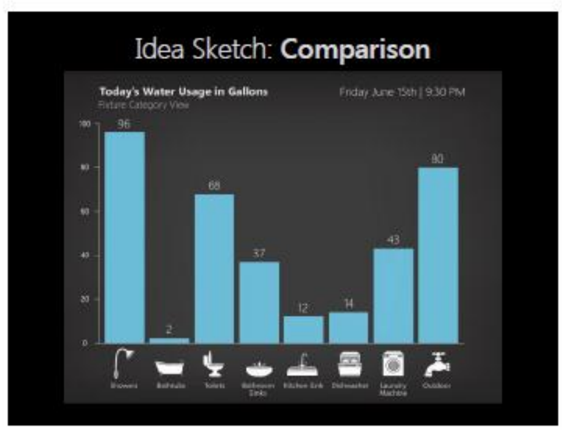

Idea Sketch: Time-Series
Water Usage in Gallons

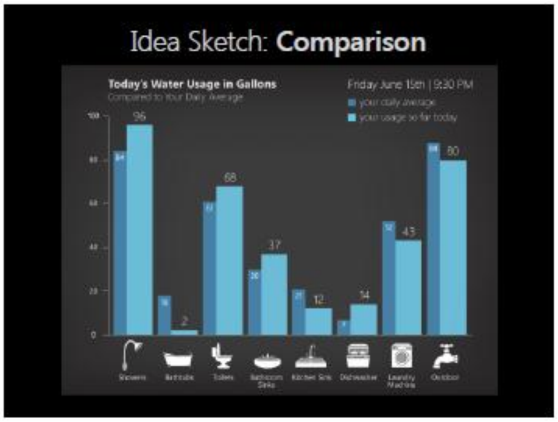

Idea Sketch: Time-Series
Water Usage in Gallons

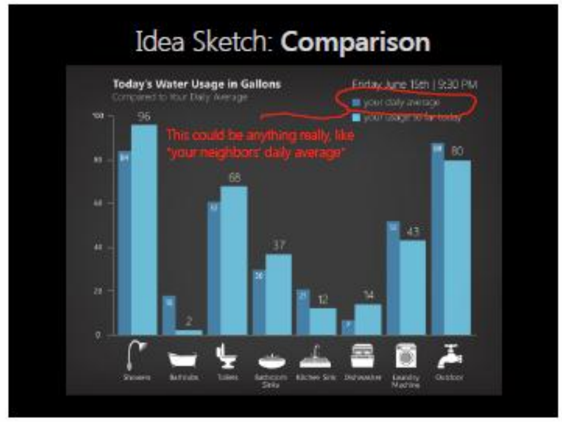

Idea Sketch: Time-Series
Water Usage in Gallons Today
Friday June 15th | 9:30 PM
Water Usage in Gallons This Year

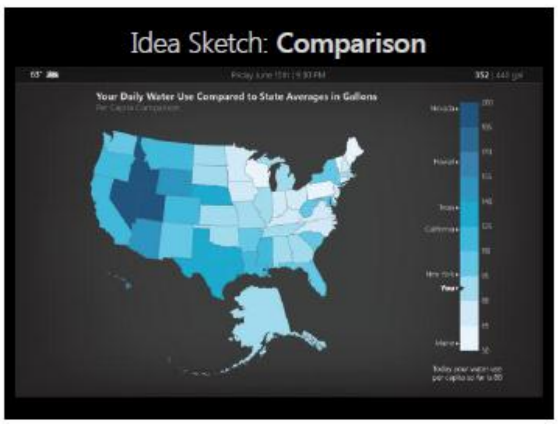

Idea Sketch: Time-Series
Today's Real-Time Water Usage
Friday June 15th | 9:30 PM

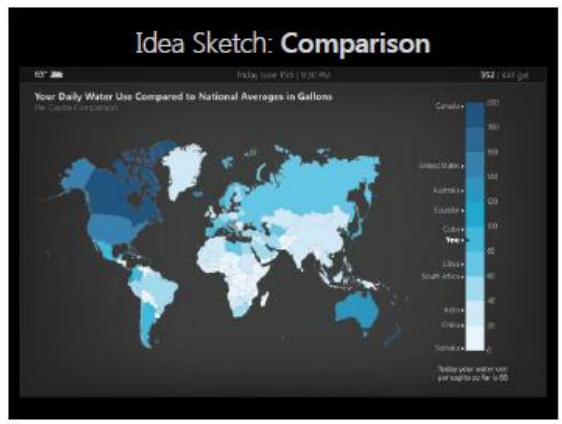

Idea Sketches
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant


Idea Sketch: Comparison
Today's Water Usage in Gallons
Friday June 15th | 9:30 PM
96
2
68
37
12
14
43
80


Idea Sketch: Comparison
Today's Water Usage in Gallons
Friday June 15th | 9:30 PM
96
68
37
12
14
43
80


Idea Sketch: Comparison
Today's Water Usage in Gallons
Friday June 15th | 9:30 PM
This could be anything really, like
"your neighbors' daily average"
96
68
37
12
14
43
80


Idea Sketch: Comparison
Your Daily Water Use Compared to State Averages in Gallons


Idea Sketch: Comparison
Your Daily Water Use Compared to National Averages in Gallons


Idea Sketches
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant


Idea Sketch: Rainflow
Today's Water Usage in Gallons
Fixture Category View
Friday June 15th | 9:30 PM
96
2
68
37
12
14
43
80

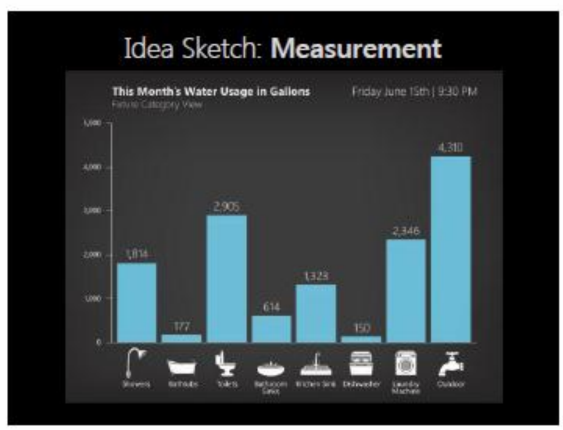

Idea Sketch: Rainflow
january 30
sunday

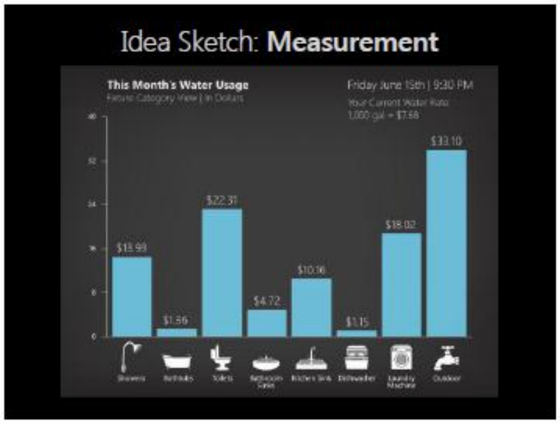

Idea Sketch: Rainflow
january 30
sunday
flow rate = recent water usage and amount
liquid level = water used today


Idea Sketch: Rainflow
january 30
sunday
daily average
goal
flow rate = recent water usage and amount
liquid level = water used today


Idea Sketch: Rainflow
january 30
sunday


Idea Sketches
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant

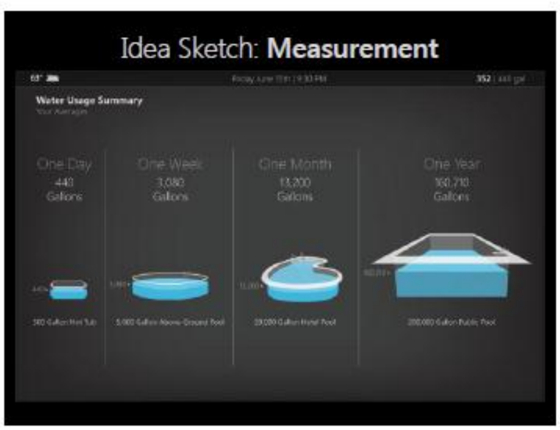

Idea Sketch: Measurement
This Month's Water Usage in Gallons
Friday June 15th | 9:30 PM
1,814
177
2,905
614
1,323
150
2,346
4,310
Showers
Bathtubs
Toilets
Bathroom Sinks
Kitchen Sink
Dishwasher
Laundry Machine
Outdoor


Idea Sketch: **Measurement**
This Month's Water Usage
Friday June 15th | 9:30 PM
$13.99
$1.36
$22.31
$4.72
$10.16
$1.15
$18.02
$33.10


Idea Sketch: **Measurement**
This Week's Water Usage in Gallons
554
2
494
282
246
40
585
875


Idea Sketch: **Measurement**
Today's Water Usage in Gallons
96
2
68
37
12
14
43
80


Idea Sketch: **Measurement**
Water Usage Summary
One Day
440
Gallons
One Week
3,080
Gallons
One Month
13,200
Gallons
One Year
160,710
Gallons


Idea Sketch: **Measurement**
Water Usage Summary
One Day
440
Gallons
One Week
3,080
Gallons
One Month
13,200
Gallons
One Year
160,710
Gallons

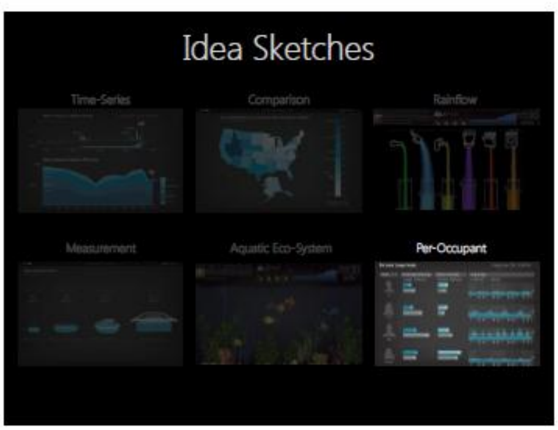

Idea Sketches
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant

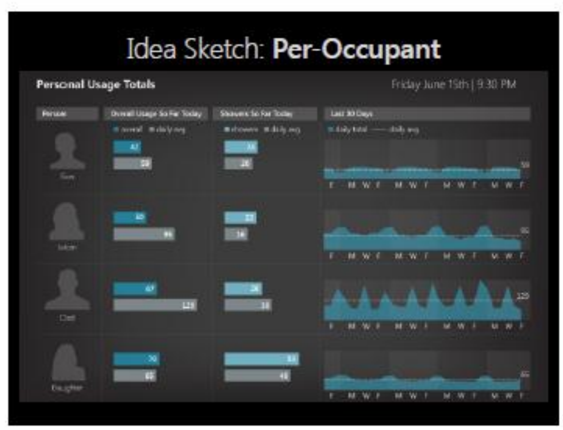

Idea Sketch: **Aquatic Eco-System**
43°
january 30
sunday
04:39PM
water savings tracker

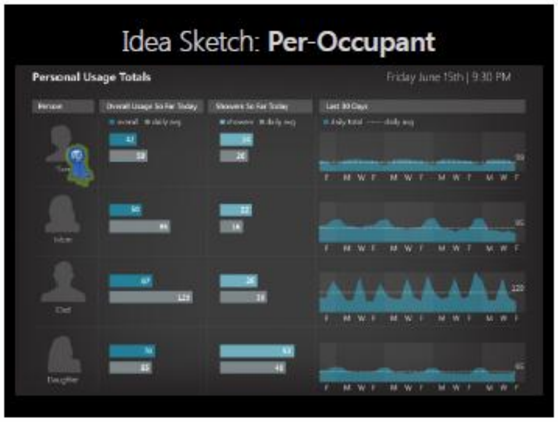

Idea Sketch: **Aquatic Eco-System**
43°
january 30
sunday
04:39PM
water savings tracker


Idea Sketch: **Aquatic Eco-System**
43°
january 30
sunday
04:39PM
water savings tracker

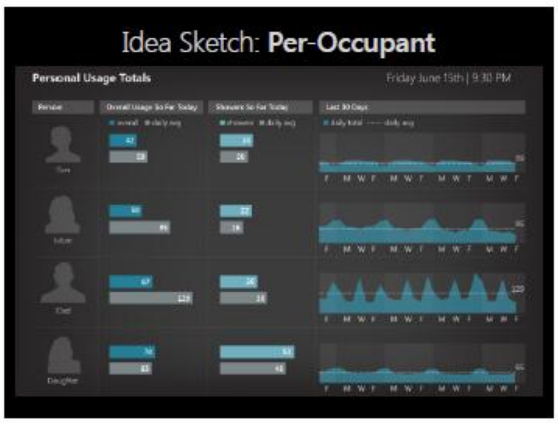

Idea Sketch: **Aquatic Eco-System**
43°
january 30
sunday
04:39PM
water savings tracker


Idea Sketches
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant

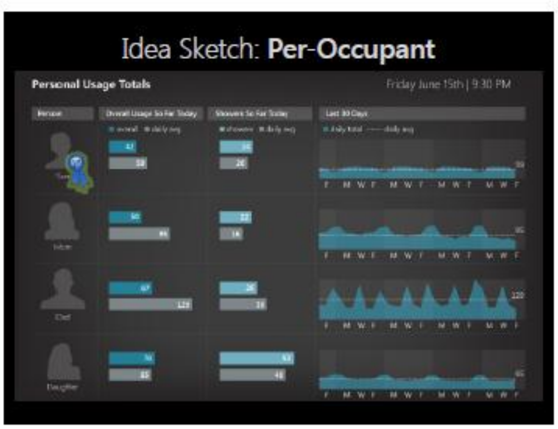

Idea Sketch: **Per-Occupant**
Personal Usage Totals
Friday June 15th | 9:30 PM
Person
Overall Usage So Far Today
Showers So Far Today
Last 30 Days


Idea Sketch: Per-Occupant
Personal Usage Totals
Friday June 15th | 9:30 PM

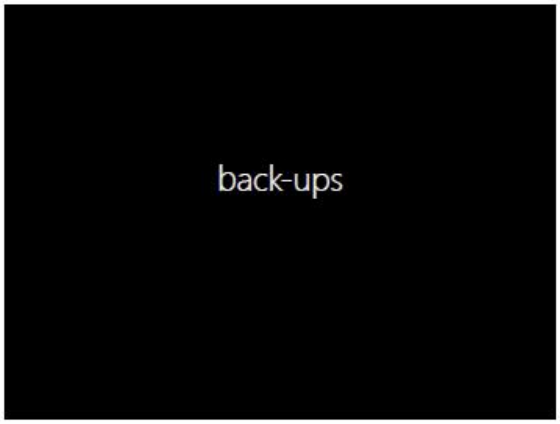

Select Three
Bar Graph
Time-Series
Comparison
Rainflow
Measurement
Aquatic Eco-System
Per-Occupant

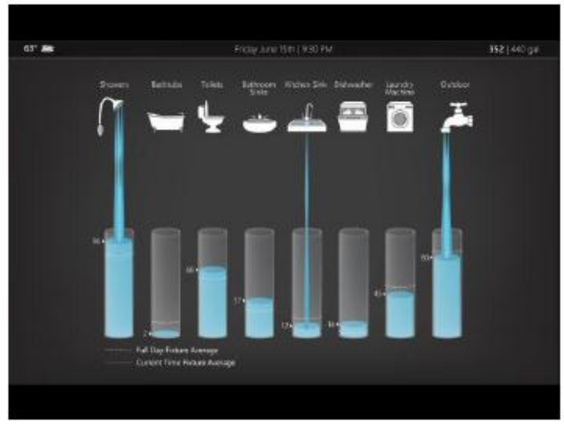

Idea Sketch: Per-Occupant
Personal Usage Totals
Friday June 15th | 9:30 PM


Idea Sketch: Time-Series
Today's Real-Time Water Usage
Friday June 15th | 9:30 PM


Idea Sketch: Per-Occupant
Personal Usage Totals
Friday June 15th | 9:30 PM

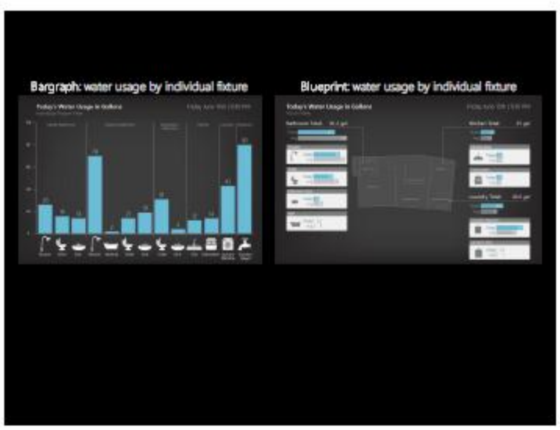

your water bill
your computer
each fixture
in-home touch
screen display

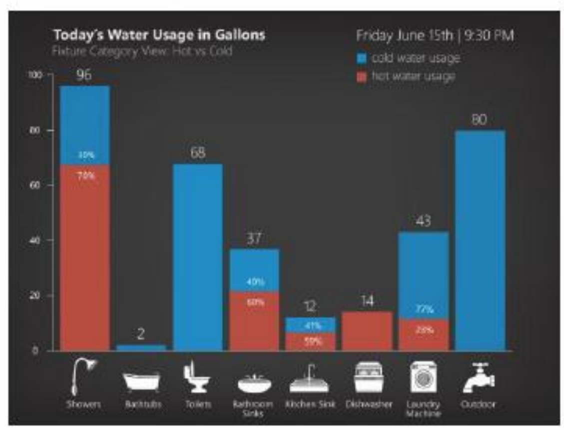

back-ups


Showers
Bathtubs
Toilets
Bathroom Sinks
Kitchen Sink
Dishwasher
Laundry Machine
Outdoor


Water Usage Summary
Friday June 15th | 9:30 PM
This Month's Usage
This Month Last Year
today
Today's Fixture Use Percentages
Today's Most Used Fixtures
Showers
Outdoor
Toilets
Shower Tips
Projection for this Month's Total Usage


Today's Water Usage in Gallons
Room View
Friday June 15th | 9:30 PM
Bathroom Total: 81.2 gal
Kitchen Total: 25 gal
Laundry Total 40.6 gal


Bargraph: water usage by individual fixture
Blueprint: water usage by individual fixture


Today's Water Usage in Gallons
Fixture Category View: Hot vs Cold
Friday June 15th | 9:30 PM
cold water usage
hot water usage
100
80
60
40
20
0
96
2
68
37
12
14
43
80
70%
60%
40%
41%
59%
28%
72%
Showers
Bathtubs
Toilets
Bathroom Sinks
Kitchen Sink
Dishwasher
Laundry Machine
Outdoor

VITA

Jon Froehlich grew up in the Midwest and wanted to be an engineer or scientist from as early as he can remember, thanks mostly to a love of Legos and an encouraging family. Jon received his Bachelor of Science degree in Computer Engineering with distinction from Iowa State University in 2001 and his Master of Science in Information and Computer Science from the University of California, Irvine in 2004 where he worked with Paul Dourish on information visualization strategies to support distributed work teams. In 2008, Jon was honored with the Microsoft Research Fellowship and in 2010, he was selected as the UW College of Engineering Graduate Student Innovator of the Year.

Jon's research focuses on designing, building, and evaluating technology that addresses high-impact social problems such as environmental sustainability, personal health and well-being, and computer accessibility. His dissertation is on promoting environmentally sustainable behaviors through automated sensing and feedback technology, which has led to a number of top-tier publications including a UbiComp 2009 best paper nomination and a CHI 2010 best paper. His work on HydroSense, an advanced water sensing system, was recently licensed to Belkin International, Inc. In 2011, Jon received his Doctor of Philosophy at the University of Washington in Computer Science and Engineering, where he was advised by Professors James A. Landay and Shwetak N. Patel.