A Large-Scale Analysis of YouTube Videos Depicting Everyday Thermal Camera Use

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ABSTRACT
The emergence of low-cost thermographic cameras for mobile devices provides users with new practical and creative prospects. While recent work has investigated how novices use thermal cameras for energy auditing tasks in structured activities, open questions remain about "in the wild" use and the challenges or opportunities therein. To study these issues, we analyzed 1,000 YouTube videos depicting everyday uses of thermal cameras by non-professional, novice users. We coded the videos by content area, identified whether common misconceptions regarding thermography were present, and analyzed questions within the comment threads. To complement this analysis, we conducted an online survey of the YouTube content creators to better understand user behaviors and motivations. Our findings characterize common thermographic use cases, extend discussions surrounding the challenges novices encounter, and have implications for the design of future thermographic systems and tools.

Author Keywords
Thermography; Thermal cameras; Sustainable HCI; OSNs; YouTube; Social media; User-generated content

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
From its faux use in movies like 1987's *Predator* [9] to its recent artistic use by the rock band *30 Seconds to Mars* [7], thermal imaging has long captured public interest. Until recently, thermographic technologies—which capture and display patterns of heat from infrared emissions—were bulky, prohibitively expensive, and intended for

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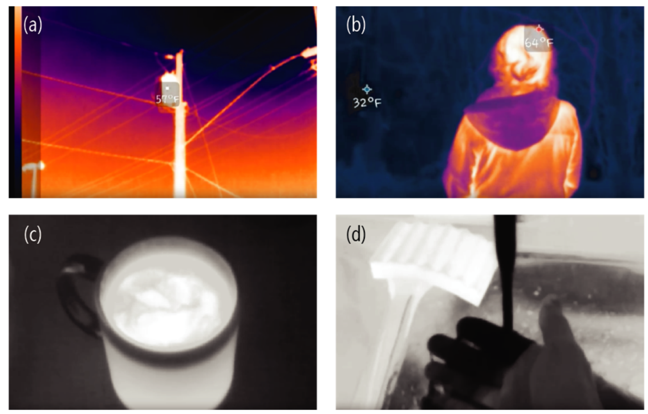

Figure 1: A *montage* video of thermal camera observations from V79 showing (a) electrical power lines, (b) a woman with a jacket outside in the cold, (c) hot coffee with cream, and (d) hand washing with cold water.

professional use [23]. Today, low-cost thermal cameras are widely available for smartphones either as mobile attachments (*e.g.,* FLIR One [35]) or, less commonly, built-in to the phone itself (*e.g.,* CAT S60 [38]). Small, inexpensive thermal sensors are also sold on "maker" electronic sites (*e.g.,* Sparkfun's FLiR Dev Kit [36]). Software development kits, interactive tutorials, and online communities have grown commensurately to share thermographic knowledge and create novel applications. Thus, what was once an expensive, expert technology is becoming ubiquitous with a growing, diverse userbase.

Despite these developments, few studies have investigated commodity thermal camera use and adoption. While our earlier work [24] investigated how novices use smartphone-based thermal cameras for energy auditing, this study was limited to 10 participants who followed pre-scripted prompts and focused on sustainability applications of thermography. In this paper, we extend and complement [24] by investigating a broader range of thermal camera use across a larger population. Specifically, we qualitatively examine "in the wild" thermal camera use as captured by user-generated YouTube videos. Our research questions are exploratory, intended to advance understanding of end-user behavior, and include: *What activities do non-professional users of mobile and handheld thermal cameras engage in and why? What level of understanding about the technology is demonstrated? How might these observations inform the design of future thermographic technologies?*

To address these questions, we collected and qualitatively analyzed 1,000 thermographic videos from YouTube. Our research methods were informed by previous work [3,4,6,14], which combine structured manual search with qualitative coding to acquire and analyze large datasets of user behavior on Online Social Networks (OSNs) (*e.g., Twitter*, *YouTube*, *Thingiverse*). To extend our dataset and manage this increased volume, we combine manual search methods with semi-automated techniques common in information retrieval. To understand and assess YouTube-user-provided questions about thermography and their answers, we also analyzed each video's comment feeds. Finally, to complement the video analysis, we invited content creators to complete an online survey about their thermal camera use, motivations, and experiences posting videos containing thermographic content on YouTube.

Our results show content creators were eager to learn about and test the limitations of their thermal cameras as well as their practice of thermography while engaging in a myriad of activities. They primarily used mobile thermal camera attachments, which were initially purchased for *purposeful activities* but were later used for *entertainment and exploration*. Content creators often engaged in uploading informal exploration videos (Figure 1)—those depicting their observations and play—as well as videos that focused on three areas: (i) building audits and urban observations, (ii) small electronic and software projects, and (iii) outdoor recreation and agricultural uses. Contrary to prior research (*e.g.,* [24]), we found few instances of novice users facing challenges around misconceptions or misinformation about thermography. When such issues did arise, the YouTube thermography community policed and corrected invalid conclusions or misuses of thermal cameras.

This work's primary contributions include the first study of "in the wild" data depicting everyday uses of commodity thermographic technology by non-professionals and a characterization of common novice uses of thermal cameras. Additionally, a secondary contribution is our extension of methods used by recent qualitative studies of data from OSNs [3,4,6,14] through the use of a hybrid manual+computational approach to dataset generation. We conclude with discussions of this approach as well as novice "in the wild" uses of thermal cameras, challenges and misconceptions these users encounter, and implications for the design of future thermographic systems and tools.

RELATED WORK

Here we provide background on thermography, describe thermographic research in HCI and ubiquitous computing, and situate our OSN-based study method in the literature.

Thermography Background

Thermal technology became commercially available in the 1960s [11] though it was expensive, bulky, and intended for professional use. Today, thermal cameras are relatively inexpensive and readily available—FLIR Systems and Seek Thermal, for example, each sell consumer thermal camera attachments for mobile devices at major retailers. These cameras are marketed for a broad range of applications including: observing wildlife, rescue operations, electrical inspections, energy audits, and medicine (see [37]).

Thermal cameras work by measuring electromagnetic radiation emitted by objects [12]. *Thermograms* combine this data with data from a conventional, co-located camera and *thermography* involves the analysis of these thermograms along with contextual factors. Unlike traditional photography, thermography requires users to account for factors that impact the accuracy of the thermal measurements. For example, every material has a specific *emissivity*—a ratio reflecting how well an object emits heat compared to a perfect emitter. Cameras must be calibrated to each material (*e.g.,* metal) being measured to obtain accurate readings. In addition, materials such as metals and glass reflect infrared radiation from their surroundings, which further complicates measurement and interpretation. Finally, environmental factors including ambient temperature and relative humidity can negatively impact thermographic scans. Given these complexities, professional thermographers are expected to complete certification programs (*e.g.,* medical practitioners [29], building inspectors [23]) before operating thermal cameras.

As thermal cameras become more widely available, prior work [23,29] has identified concerns regarding their use by untrained operators (*e.g.,* misinterpreting thermal imagery, spreading misconceptions). For example, since thermal cameras allow users to "see in the dark," they can be confused with light amplifying technologies associated with "night vision" [31]. Another common misconception, which we confirm through our study, is the belief that thermal cameras can see through objects such as walls or clothing [23]. Yet, thermal cameras only measure surface temperatures—any visible patterns depict the way heat moves through a subject's internal structures to its surface (*e.g.,* thermal cameras can locate wall studs as they transfer heat to/from the wall surface differently than the surrounding areas). In response, one aspect of our work explores these issues and concerns.

Thermographic Research in HCI and Ubicomp

HCI researchers are increasingly using thermal cameras to support novel interactions (*e.g.,* gesture recognizers [1], smart surfaces [19]) and to perform domestic sensing (*e.g.,* monitoring energy use [34], creating interactive city lighting [27]). Closest to our work is that of Mauriello *et al.,* which focuses on the building science and energy auditing applications of thermography in HCI [21,23,24]. One of their recent studies asked ten novice users to explore their lives with a provided thermal camera attachment and complete semi-structured energy auditing tasks [24]. While this study generated insights into how minimally trained novice users might approach energy auditing tasks using thermography, a comprehensive picture of novice use of thermal cameras was not investigated. Characterizations of "in the wild" uses of these devices would facilitate the development of methods and tools that support the public's needs including helping them better understand the data they collect. In this work, we form such a characterization by looking at user-generated content on YouTube.

"In the Wild" Studies via OSNs

Recent studies have demonstrated the value of exploring large amounts of user-generated content qualitatively, such as how YouTube videos can provide insights into users' natural technology interactions [3,6,14]. Moreover, these studies reach large swaths of end-user populations who may otherwise be difficult to observe (*e.g.,* how people with motor impairments use touchscreen devices in their homes [3]). Qualitatively analyzing data from OSNs can nonetheless be challenging: query results can be large (*i.e.,* in the thousands or more) and noisy [32]. To mitigate these challenges, researchers have examined a single query and downsampled the results [4] or conducted multiple queries using a systematic search strategy on highly specific topics [3,6]. In our work, we combine these strategies with computational methods to broaden our dataset, ensure high relevance, and reduce manual labor.

METHOD

Similar to previous qualitative studies of user-generated content on OSNs [3,6,14,26], this study was conducted in three stages: first, we *generated a dataset* containing OSN data relevant to our research target domain—in this case, videos featuring novice use of thermal cameras. Second, we *qualitatively analyzed video content* along multiple dimensions. Finally, we conducted an *online survey* soliciting additional information from content creators (*i.e.,* the persons who posted the YouTube videos).

Dataset Generation

We generated our dataset using SMIDGen (Scalable, Mixed-Initiative Dataset Generation) [22], a hybrid manual+computational approach to collecting large amounts of relevant, OSN-sourced data. SMIDGen has four steps: (i) manually exploring an OSN to generate an initial set of keywords, queries, and data, (ii) computationally expanding these queries to increase domain/topic coverage, (iii) mixed-initiative data labeling and training to construct automated models, and (iv) applying these models at scale to generate a large, diverse, but still relevant, final dataset.

Step 1: Creating an Initial Dataset. In July of 2017, we searched YouTube for the quoted string "thermal camera" alone and in combination with keywords representing common thermographic applications (*e.g.,* "building", "medical"). We manually assessed the search results to construct a list of general thermography-related search terms (Table 1). Next, we queried these terms via the YouTube Data API (v3) to create an initial dataset. Following Anthony *et al.* [3], we extracted the first 200 YouTube results for each term and stored the resulting video URL and metadata (title, description, view counts, *etc.*). In all, our search results contained 1,400 videos, which was reduced to 1,092 after removing duplicates.

Step	Terms
Step 1: Initial Keywords	infrared, lepton, thermal, thermal camera, thermal image, thermal imaging, thermography
Step 2: Expanded Keywords	breast thermography, flir lepton, flir one, flir thermal, imaging camera, infrared camera, infrared thermography, night vision, seek thermal, thermal imager
Step 3: Iterated Codebook	everyday use, product review, news coverage, unboxing, professional demo, advertisement, off topic

Table 1: The search terms and training data codebook used to assemble our study dataset throughout SMIDGen's four steps.

Step 2: Automatically Expanding the Dataset. To identify keywords that YouTube content creators commonly used to describe their videos in addition to the keywords we generated, we applied two standard query expansion algorithms: word co-occurrence and Kullback-Leibler Divergence [18]. After applying these algorithms to the 1,092 videos' titles and descriptions in our initial dataset, we merged the top ten keywords from each method and identified 13 new, unique search terms [8]. We queried each new keyword alone and in combination with the initial keywords then extracted the top 200 videos in each query (similar to [3]) to capture videos our initial search may have missed. This process generated an expanded dataset of 6,790 unique, potentially relevant videos.

Step 3: Mixed-Initiative Analysis and Modeling. Keyword-based queries are imprecise, thus a subset of these 6,790 videos are expected to be irrelevant to the thermography domain. Even within the thermography domain, specific types of videos were *off-topic* for our research questions (*e.g.*, product reviews or unboxing videos don't portray everyday use of this technology). Manually filtering thousands of videos for *relevance* (*i.e.,* thermal camera use) and *topic* identification (*e.g.,* everyday use) is time- and labor-intensive. To accelerate these tasks, we used a mixed-initiative approach that employed classification algorithms to learn what constitutes relevant and topical videos. To create training data for these classification algorithms, two research assistants iteratively coded the initial dataset from Step 1 using the traditional coding process in [5,15]. We began with a modified codebook from [4], which offered high-level codes typifying smartphone use videos on YouTube (Table 1). Video titles, descriptions, and the content were used as input. Each video was labeled with a single category and Cohen's kappa was used to calculate inter-rater reliability (IRR). After three rounds of coding, each on 200 randomly selected videos, average IRR across codes was 0.69 (*SD*=0.09), considered *good agreement* [33]. The research assistants then divided and coded the remaining Step 1 data (*N*=1,092).

This data was then used to train a machine learning classifier to complete the *relevance* and *topic* filtering tasks. To convert YouTube videos into a training samples, we featurized the videos by converting their titles and

Topic Codes	Sub-Topic Codes
Content Areas (*N*=10)	Building and Urban Environments, Health and Wellness, Paranormal Investigations, Electronics and Software Projects, Recreational Outdoor Activities and Agriculture, Informal Exploration, Pollution Activism, Vehicles, Research, Security and Emergency Services
Misconceptions (*N*=6)	See Through Objects, Measure Air Temperature, Measure Gases, Faux Filters, Faux Thermal Imagers, Camera Operation Issues
Comments Containing Q/A (*N*=4)	Content Questions, Technical Specifications, Follow-up Request, Other

Table 2: Topic and sub-topic codes applied to analyze the content of "everyday use" videos.

descriptions into a bag-of-words model and re-weighting terms using term-frequency, inverse-document-frequency (TF-IDF) to reduce the weights of common keywords, as is standard in information retrieval research [8]. Following an evaluation of several classification algorithms (see [22] for an in depth description of this process), we selected a Random Forests model to identify domain *relevance* (*e.g.,* is the video about thermal camera use) and the Logistic Regression model to identify specific sub-*topics* (*e.g.,* everyday use). Using 10-fold cross-validation, the accuracy of the *relevance* and *topic* classifiers were 0.91 and 0.73, respectively. The topic classifier's lower accuracy is to be expected since the semantic similarity between in- and out-domain videos is likely much lower than in-domain videos of different topics (*e.g.,* an irrelevant video about gaming likely has fewer words in common with a thermography video than a video about unboxing a thermal camera has with a video about using that camera to observe heat loss in a home). Furthermore, to avoid accidental omission of "everyday use" videos, we chose to prioritize recall over precision to obtain potentially more diverse data from the *topic* classifier. As researchers would later review videos classified as "everyday use" and remove off-topic videos at that stage, this prioritization should not impact results.

Step 4: Applying Classifiers and Final Dataset. Finally, we applied these classifiers in sequence—*relevance* filtering then *topic* identification—to the unlabeled data from Step 2. We manually validated the output of 200 randomly sampled videos from each classifier, finding the *relevance* and *topic* accuracy to be consistent with the F1 scores. Our final labeled dataset included 1,686 videos from 772 human-labeled videos and 914 machine-labeled videos. From this set, we randomly sampled 1,000 videos for content analysis—a quantity we desired to ensure topic saturation.

Qualitative Analysis of "Everyday Use" Video Content

We qualitatively analyzed the 1,000 sampled videos to investigate our research questions regarding how and why people use thermal cameras. We coded the videos using a combination of inductive and deductive codes by using the video titles, descriptions, content, and comments. Non-everyday use videos were coded as "off-topic" and no further action was taken. The codebook (Table 2) included 16 dimensions across two topics: content areas (*e.g.,* outdoor recreation, agriculture) and misconceptions (*e.g.,*

Categories	Dataset (N=675)	Average Duration (SD)	Median Views	Contains Misconceptions	Q&A in Comment
Informal Exploration	46.5% (314)	2.28 (5.11)	507	9.8% (31/314)	27.7% (87/314)
Outdoor Recreation & Agriculture	16.1% (109)	3.24 (7.50)	807	0.9% (38/109)	34.8% (38/109)
Electronic or Software Project	11.9% (80)	3.03 (4.70)	368	1.2% (1/80)	28.7% (23/80)
Buildings and Urban Observations	11.1% (75)	3.06 (4.11)	351	4.0% (3/75)	24.0% (18/75)
Vehicles	6.5% (44)	1.90 (2.48)	822	0.0% (0/44)	27.2% (12/44)
Paranormal Investigations	2.8% (19)	4.30 (4.25)	2327	10.5% (2/19)	63.1% (12/19)
Emergency Applications	2.1% (14)	1.09 (1.05)	637	7.14% (1/14)	28.5% (4/14)
Health and Wellness	1.8% (12)	5.19 (7.49)	2116	0.0% (0/12)	0.3% (4/12)
Research	0.9% (6)	1.02 (0.80)	385	0.0% (0/6)	16.6 (1/6)
Pollution Activism	0.3% (2)	0.34 (0.03)	103	0.0% (0/2)	0.0% (0/2)

Table 3. The categorical results from our coding process sorted by frequency; categories were exclusive.

thermal cameras can see through walls). Videos containing questions (*e.g.,* in the video description, in the comment feeds) were further analyzed across 4 dimensions (Table 2) describing the question content. When determining in what activities non-professional users most often engaged, we coded each video for its primary content (*i.e.,* the activity that took up at least 80% of video's duration).

Two researchers randomly selected and coded 20% of the data (200 videos), achieving an initial IRR of 0.68 using Cohen's kappa [33]. After resolving disagreements and clarifying the codebook, the researchers coded a new, randomly selected 20% sample of the data and achieved an average IRR of 0.75 (*SD*=0.27). After resolving differences, the remaining 600 videos were split between the researchers and coded independently. Ultimately 67.5% (675/1,000) of the videos in our dataset depicted *everyday use*, the rest being thermography videos with other focuses (*e.g*., marketing, professional services). Our findings will focus on the content, misconceptions, and community responses around these 675 videos.

Comment Feed Analysis. We performed an additional analysis of the 199 (29.4%) videos that contained questions in either the video description or posted in the comment feed. For each video, we reviewed questions asked within the top 20 "most popular" comments. Questions from content categories accounting for ≥10% of the dataset (166 videos, Table 3) were coded into four categories:

- **Content questions** about the video's subject matter (*e.g.*, *"Aren't hornets cold blooded?"*)

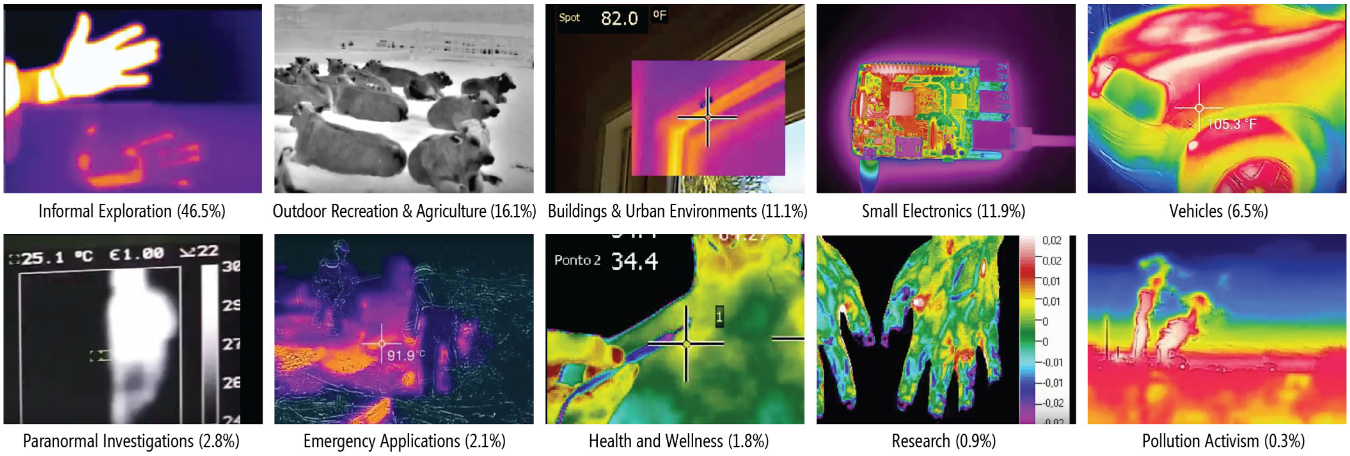

Figure 2: The images above portray a typical video from each coded category and the category's percent representation in the overall dataset (N=675).

- **Technical specification questions** about the devices being used or the process of making the video (*e.g., "What kind of camera did you use?"*)
- **Follow-up requests** to make more videos on the same or different topics (*e.g., "Can you do a video on the heat emitted by cellphone usage?"*)
- **Other questions** (*e.g., "What is this music playing?"*)

Moreover, for each question we recorded whether an answer was posted and, if so, who the respondent was: the original poster of the video, other YouTube users, or both. We analyzed the correctness of responses related to thermographic misconceptions but not for more general discussions (*e.g.,* camera costs, background music titles).

Online Survey

To complement our qualitative video analysis, we surveyed YouTube content creators with videos in our dataset. The online survey asked about demographic information, reasons for owning a thermal camera, usage patterns, motivations for posting videos online, and perceived benefits from engaging with the YouTube community. As a related thread of our work is focused on the role of thermal cameras in energy auditing, we also asked what impact, if any, thermal cameras had on building improvements or energy usage. The survey included 5pt-Likert questions, check-all-that-apply questions, and open-ended, short-response questions. We contacted all unique content creators (N=1,023) in the final everyday use dataset generated in Step 4 of our dataset generation process using YouTube's direct message feature and a pre-scripted macro. Participants who completed the survey and opted to voluntarily disclose contact information were entered in a raffle for one of two $20 Amazon gift cards. In all, 78 participants (7.6%) completed the survey, which had an average completion time of approximately 8 minutes.

VIDEO ANALYSIS FINDINGS

We report on the most common everyday uses of thermal cameras shown in YouTube videos (N=675), when misconceptions occurred, and the information users exchanged in question and answer discourses. Overall, we found four primary uses of thermal cameras and a knowledgeable base of users who respond to questions and provided information. Quotes from content creators—transcribed or from video descriptions—and commenters are attributed using a 'V' followed by the video number.

Common Thermal Camera Usage Activities

The most common thermographic videos focused on informal exploration (46.5%), outdoor recreation and agriculture (16.1%), electronic and software projects (11.9%), as well as building energy audits and urban observations (11.1%). Less frequent categories (<10% of the dataset) included vehicles, paranormal investigations, emergency applications, and health and wellness (Table 3). The average video duration was 2.7 minutes (SD=5.3 min), and most covered a single thermal observation (*e.g.,* coffee brewing). Figure 2 provides examples of these categories and below we expand upon the four most common.

Informal Exploration

Nearly half of all everyday use videos (46.5%, 314/675) were *informal explorations* (314/675). Many (19.1%, 60/314) of these videos focused on how an individual phenomenon appeared in infrared (*e.g.,* nostril temperature when breathing, setting a ping pong ball on fire, thermal handprints on different surfaces, running water in sinks or over a person's hands). While the subject matter was very diverse, some of the most common observations within this category included household pets (9.9%, 31/314), filming the user's face (8.9%, 28/314), coffee cups and brewers (8.2%, 26/314), running water in sinks and bathtubs (4.4%), and children (2.2%, 7/314). Other interesting, but less common, subject matter included crushing objects in a hydraulic press and looking at the heat dispersion, throwing liquid nitrogen down a hallway, recording the effects of incendiary devices (*e.g.,* model rockets, fireworks), and observing the extrusion process of 3D printers. Some content creators chose to create *montage* videos (14.6%, 46/314) to call attention to the diverse phenomena they investigated with their thermal cameras (*e.g.,* a user filming a coffee pot, then looking at an electrical appliance, then an

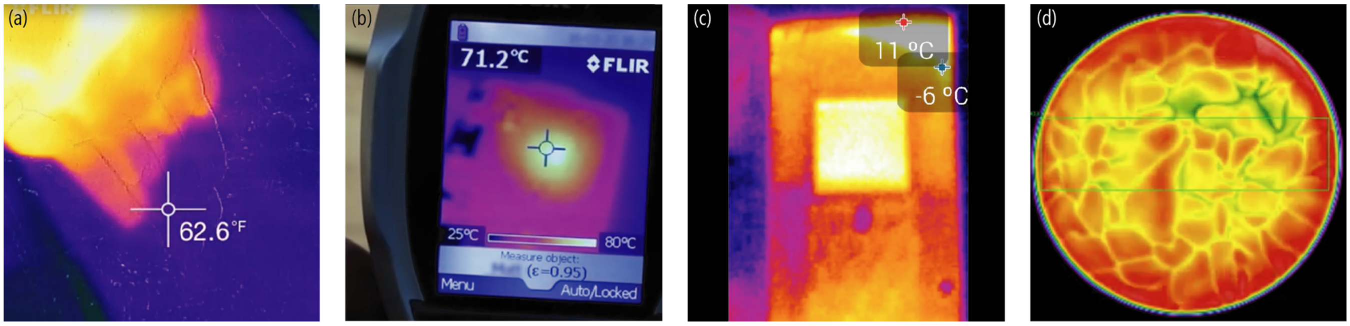

Figure 3: Illustrative examples described throughout our findings: (a) exploring whether thermal cameras can see through water in V90, (b) comparing a Raspberry Pi's internal temperature sensor to a handheld thermal camera reading during a stress test in V801, (c) an exterior home inspection in V351, and (d) describing how convection in hot coffee causes cells to be visible in thermal images in V154.

insulation problem in the home; Figure 1). These montages occasionally featured short segments related to other content areas (*e.g.,* wildlife, electronics), but still emphasized exploration.

Testing Technical Limits. Another common type of informal exploration was testing the technical limits of the thermal camera (11.8%, 37/314) by, for example, walking away from the camera to test its detection range and clarity. These videos typically explored how well a thermal camera could distinguish objects at various distances as well as the properties of different materials (*e.g.,* reflectivity of glass). For example, one video asked, "*Can a Thermal Camera See Through water?*" (V90, Figure 3a):

> *"I'm going to dip my hand down into the aquarium, right into the water on the top, and let's see what happens. I'm going to calibrate the camera first and dip my hand in the water.*
>
> *(Dips hand in aquarium.)*
>
> *Yeah the surface of the water really reflects the heat away. But we can actually see my hand is heating the very surface of the water. […] So yeah, the thermal camera doesn't see through water very well, but it is sensitive enough that you can actually see my hand warming up the water. Pretty cool." (V90)*

Videos investigating if or how well a thermal camera could "see in the dark" were also relatively common (12.8%, 40/314). Some experiments had targeted applications, such as parents attempting to observe whether their children were sleeping without turning on the lights or a father mounting his thermal camera to a UAV to find a child's lost headband in the backyard at night.

Outdoor Recreation and Agriculture

Outdoor recreation and agriculture was the second most common type of video (109/675; 16.1%). This included passively observing farm animals and wildlife (42.2%, 46/109) and hunting (*e.g.,* deer, boar) (22.9%, 25/109). For example, the creator of V668 stated: *"I see many birds while hiking with the thermal imager at night. Most are sleeping, some are nocturnal."* Other activities included walking dogs (9.2% 10/109), cloud watching (8.3%, 9/109), and beekeeping (10.0%, 11/109).

Electronic and Software Projects

Electronic and software projects was the third most common (11.9%, 80/675) and most often featured time-lapses of how electronic devices managed heat (38.8%, 31/80)—either heating up, cooling down, or ventilating heat during operation. In V801 (Figure 3b), for example, one content creator compared a Raspberry Pi's internal temperature sensor to a thermal camera reading during a stress test:

> *"The temperature spikes up quite quickly and you'll notice when it hits the 80C mark it starts to throttle the speed. [However,] the temperature outside on the chip is significantly higher as you can see." (V801)*

Videos in this category also showed users specifically diagnosing issues (22.5%, 18/80) such as a missing component on a printed circuit board: *"Now that we have a thermal camera we can see that the card quickly detects that there is no heatsink and [it] throttles itself to prevent damage"* (V572). Finally, a few videos (18.9%, 15/80) demonstrated using thermal cameras as a sensor for a software project. Notable examples included detecting cars in the street and using thermal input for an interactive table.

Building Energy Audits & Urban Observations

Finally, building energy audits and urban observations comprised 11.1% (75/675) of the everyday use dataset. During home inspections, users either performed a general walkthrough of their home or focused solely on a problem area. They investigated large appliances (18.9%, 14/75) (*e.g.,* as in V199 of a faulty radiator), hidden structures (14.7%, 11/75) (*e.g.,* wall studs, insulation issues), electrical panels (10.7%, 8/75), air leakage around windows or doors (10.7%, 8/75), and moisture issues (2.7%, 2/75). General urban observations (*e.g.,* train yards, people walking on city streets) made up 10.7% (8/75) of videos in this category.

Some users (13.3%) seemed to be knowledgeable about how environmental factors may influence their inspections. For example, the user in V548 stated: *"I'm out here early for a reason, this wall catches all the afternoon sun."* implying that later scans would be problematic because solar loading would impact measurement accuracy.

Similarly, in V351 the user described the importance of temperature differentials for proper energy audits of building envelopes (Figure 3c) [16]:

> *"I used my new Seek Thermal camera [...] to look at the exterior of my house when it was -19C outside. You can see the heat loss of my foundation, the front door, and my 20+ year old single pane windows." (V351)*

Other Video Categories

The remaining six categories each accounted for ≤10% (0.2-6.5%) of our dataset and are briefly summarized here. For vehicles (6.5%, 44/675), videos included passive observation of vehicles in motion, actively diagnosing component issues (*e.g.,* defective heating coils in a steering wheel), or engines heating up. Paranormal investigation videos (2.8%, 19/675) showed users exploring ghost sightings, tracking UFOs, and looking for Bigfoot. Health videos (1.8%, 12/675) focused on the potential diagnostic properties of thermography, such as checking body temperature or detecting cancerous growths near the skin's surface. Finally, two videos focused on energy production plants and were coded as pollution activism (0.3%, 2/675).

Misconceptions

We found four types of misconceptions about thermography and three types of technical misconceptions, which were present in 5.3% (N=36) of the videos. For each video we reviewed the comment thread to determine whether the misconception was corrected by another member of the community.

The most common thermography misconception (31.4%), which was likely satirical, suggested that consumer thermal cameras could image flatulence. These videos were strongly rebuked by commenters who described the inability of standard thermal cameras to observe gases. The second most common misconception (19.4%) was that thermal cameras could directly measure ambient air temperatures by viewing the effects of hot/cold air on a surface or imaging condensation (*e.g.,* a person heavily exhaling in the cold and imaging the moisture vapor). Again, in all cases, this misconception was corrected in the comments section. Third, 13.8% of videos claimed that thermal cameras could "see through" clothing or walls; however, as mentioned previously, thermal cameras can only measure surface temperature. For instance, the "see through" effect of clothing does not actually show a naked person, but instead highlights areas where body heat transfers through layers of clothing differently—which, perhaps, is a type of "see through" behavior in colloquial terms. Fourth, 11.1% of videos exhibited confusion about IR reflection when imaging glass or other surfaces. Again, all these misconceptions were typically corrected by other YouTube users in the video's comment section.

Misconceptions about what constituted thermal imagery or devices also existed: 13.8% of videos were made with faux thermal photo filters and 5.8% described homemade "near-infrared" thermal imaging devices that were made by modifying cameras (to remove infrared light filters). The latter was most likely a misnomer rather than an explicit misconception but could promote the concerns mentioned in [31]. Finally, a few videos (5.5%) demonstrated general confusion about the camera's features (*e.g.,* why were the camera's conventional and thermal images misaligned).

Question Type	Number Asked	Number Answered	Who Responded		
			Original Poster	Other Poster	Both
Technical Specification	41.9% (153/365)	53.6% (82/153)	75.6% (62/82)	12.2% (10/82)	12.2% (10/82)
Content	29.9% (109/365)	58.7% (64/109)	62.5% (40/64)	12.5% (8/64)	25.0% (16/64)
Other	19.5% (71/365)	71.8% (51/71)	55.9% (28/51)	21.6% (11/51)	22.5% (12/51)
Follow-Up Request	8.8% (32/365)	50.0% (16/32)	62.5% (10/16)	18.7% (3/16)	18.7% (3/16)

Table 4. Comment breakdown.

YouTube Comment Threads

To understand the types of discussions that occur around thermal videos posted to YouTube, we coded all 675 videos for whether they contained question-and-answer discourse—see Table 3. Below, we focus on the 166 videos that had Q/A comment threads across the top four video categories. Across these videos, we found a total of 365 unique questions, concerning topics such as: *technical specifications* (41.9%), *content* (29.9%), *other* (19.5%), and *follow-up requests* (8.8%,). For example, a typical technical specification Q/A comes from V359:

> Commenter: *"Any way to calibrate the sensor? That would remove the "noise curtain"*
>
> Response: *"I think with the proper software, this would be more than possible, no idea if you can calibrate the sensor to the exact temperature, but there must be a way to remove the noise, especially at low delta-T, where it occurs most [...] Convenient thing there is a free SDK to Therm-App owners."* (*V359*)

For content, a YouTube commenter asked about the bubbling surface of a coffee cup (V154, Figure 3d):

> Commenter: *"what is [does] this mean????"*
>
> Response: *"This is what happens in every cup of coffee. [...] This video demonstrates a phenomenon of convection into the water, i.e. interfusion of more cold layers on the water surface and more hot layers in the deep of the water. As a result, we can observe cells on the water surface in infrared frequency band." (V154)*

While more than half of all questions were answered (58.4%), questions categorized as *other*—which tended to be less specific to the video (*e.g.*, "what song is this?")—received markedly more responses than other question types (71.8%, Table 4). Across all questions, the original content creator, alone was most likely to respond (Table 4):

> Commenter: *"Can you do a video showing the sky. I can't find any videos showing the sky. I'm a sky watcher and am thinking of getting a thermal device."*

Response: *"Thermal isn't really good for skywatching unless you are looking at clouds. Water vapor tends to show, and it [is] generally very cold. Almost always black compared with terrestrial objects other than clouds or aircraft" (V79).*

Despite this activity, over half of the questions (58.4%) asked across the 166 videos remained unanswered due to low interaction with the community (*e.g.,* no comments).

ONLINE SURVEY FINDINGS

To complement the video analyses and to better understand thermal camera use and motivations for sharing on YouTube, we invited content creators to complete an online survey. We contacted 1,023 unique YouTube users across the final video dataset and received 79 completed surveys (a response rate of 7.7%). As our focus is on novice use, we report on the 48 respondents who stated that they do not use a thermal camera professionally. Participants are identified by "P" and their survey number (*e.g.,* the 13th survey respondent is identified as P13). Some percentages do not add to 100 due to check-all-that-apply questions.

Demographics. All survey respondents were male (100%, 48). Their average age was 39.3 years (*Mdn*=39, *SD*=11.0, *range*=20-68). Most respondents held an advanced degree (60.2%) or had completed vocational certification programs (10.4%); all others had a high school diploma (29.1%). Respondents largely reported technical professions, including: various kinds of engineers (29.1%), information technology specialists (22.9%), and security professionals (10.4%). There were also teachers (8.3%), students (4.1%), and other professionals (*e.g.,* martial arts instructor). Most participants were concerned about climate change (*Mdn*=4, *M*=3.4, *SD*=3.5), rated on a 5-pt Likert scale (with '5' being "extremely concerned"); we used this as a proxy for assessing eco-consciousness, as a primary use of thermography is energy auditing.

Thermal Camera Use. Most respondents used thermal camera smartphone attachments (52.0%)—specifically the FLIR ONE (33.3%) and the Seek Thermal Compact (18.7%)—or handheld thermal cameras (15.5%). Others used the CAT s60 smartphone with a built-in thermal camera (4.0%), the Lepton module for Raspberry Pi (2.0%), and the Tau640 for UAVs (2.0%). When asked why they *initially acquired* a thermal camera (Figure 4), almost half (45.8%) reported purchasing for energy auditing, followed by wildlife observation and outdoor recreation (33.3%), nighttime navigation (22.9%), security (14.5%), culinary (4.2%), and agriculture (2.0%). Respondents (60.4%) also reported purchasing their camera for "other" activities, including: for curiosity or fun, electronics testing, ghost hunting, and flying UAVs. When asked about *actual post-purchase uses*, responses for security increased (+8.3%) as well as energy auditing (+6.2%), culinary (+6.2%) and outdoor recreation (+2.0%) activities. However, nighttime navigation and agriculture use both fell (-4.1.0% and -2.0%, respectively). Additionally, the quantity of "other" uses also fell (-14.5%), but new uses from the write-in responses emerged (*e.g.,* pest control, monitoring 3D printers) and some respondents offered reasons why they discontinued use. As P39 described, the thermal camera was *"…not as good for wildlife observations as I would have thought.*"

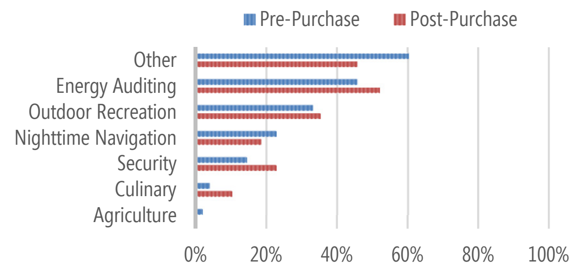

Figure 4: Survey participant's planned (pre-purchase) and actual (post-purchase) thermal camera activities in terms of percentage of total respondents (*N*=79).

To get a sense of how often respondents used their thermal cameras for these activities, we asked them to rate their use on a 5-pt Likert scale ordered daily to never. Most reported using their cameras monthly (39.5%) followed by semi-annually (25%), weekly (18.7%), then daily (12.5%).

Experience with YouTube. Most respondents commented that their reason for sharing videos on YouTube was to educate or share with the YouTube community (45.8%). As P79 said, "*[I post] for views and science".* Other reasons included for fun (22.9%) or to show friends and family (8.3%) while the remaining (23%) provided non-descript or unclear responses (*e.g.,* "*because I can*"). Many seemed to find the content of their videos fascinating, stating they shared their videos and images "*to show things you can never see without a thermal camera*" (P32). Half our survey respondents (50.0%) reported interacting with other users on YouTube including engaging in commenting, receiving requests for follow-up videos, and providing feedback—which is consistent with our earlier comment analysis. Most participants at least somewhat agreed (58.3%) that the feedback they received on YouTube was valuable or personally beneficial, almost a third (29.1%) were neutral, and three (6.25%) disagreed.

General Thoughts on Thermography. Overall, most respondents (97.9%) agreed that their thermal camera was a useful tool and half (47.9%) strongly agreed. Almost all participants (95.8%) agreed that their camera was helpful in discovering new things about the world around them and ~half (47.9%) strongly agreed. Similarly, most participants (95.8%) agreed that they would continue to use their thermal camera in the future and half (50.0%) strongly agreed. Finally, 85.4% expected to continue sharing their thermal content on social media.

Building Thermography. While 45.8% of respondents mentioned energy auditing as a specific motivation for purchasing a thermal camera, a higher percentage (52.0%) reported using their device in this way after purchase. Participants who used their camera for building thermography inspected a wide variety of building types, from single-family homes (85.7%) and multi-unit dwellings (28.6%) to commercial buildings (14.3%) and schools (8.6%). Inspection tasks included: observing air leakages (71.4%), insulation checks (71.4%), electrical issues (57.1%), moisture inspections (40.0%), or locating hidden structures (34.2%) such as hot water pipes or wall studs.

When asked about why they performed thermographic inspections of buildings, most respondents (86.9%) cited saving on utility bills, energy conservation (*e.g.,* finding leaks, supporting winterization efforts) or both, while the rest (17.1%) cited curiosity. A few participants (5.7%) reported using their imagery to supplement claims against landlords or home improvement companies. For example, as one respondent explained:

> *"I had new windows installed that appeared to be leaking air. A home inspection was $450, a thermal imager was $300 and given that I know how it works it was an easy choice. [The] window installer had to do warranty work that they didn't initially agree with." (P3)*

Overall, most respondents were positive about the outcomes of their building thermography activities. Based on their inspections, more than half (60% or 21 respondents) reported making decisions to pursue renovations or retrofits. All agreed that these building improvements directly resulted in saving money on utility bills and almost a third (28.6%) strongly agreed. Fewer agreed (71.4%) that these renovations or retrofits led to improvements in the building's thermal comfort. Most (71.4%) did not agree that engaging in building thermography had resulted in any new conservation behaviors, but those that agreed believed that these behavior changes had led to both energy savings and improvements in thermal comfort.

DISCUSSION

Through a mixed-methods approach of analyzing OSN video data, comments, and an online survey with content creators, our work advances understanding of non-professional use and conceptions of thermography. Below, we reflect on major findings, present design recommendations, and discuss our study methodology as well as key limitations.

Novice Uses of Thermography

Much like previous work investigating technology use via OSNs [3,4,6,14,26], we found that user-generated videos offered an otherwise inaccessible window into user behavior of an emerging technology. In particular, novice users expressed positive attitudes toward thermal cameras and performed diverse activities ranging from imaging pets and beverages to investigating electrical failures and home improvements (*i.e.,* the need for or success of a repair).

Thermal cameras provided not just a new avenue to explore the world but also, in some cases, supplied important information that helped users diagnose problems and support decision making. We found that 60% of survey respondents performed home renovations based on their self-diagnostics. Videos also showed users utilizing thermography as a visual aid during electrical and agricultural inspections.

Contributing to the YouTube Thermography Community

This work also offers insights into why these users chose to post videos and engage with YouTube. We found that users engaged in rich dialogues about thermal camera use and limitations through YouTube videos and comment feeds. Our survey and comment analysis revealed both intrinsic and extrinsic motivations to participate in the online community similar to [20,25]. Content creators reported posting videos to help showcase a particular thermal camera application, to explore a specific phenomenon, and/or to help teach others. Users reported enjoying sharing content and believed that this content would attract viewers. As P79 summarized, he shared videos "*for views and science*."

Novice Understanding of Thermography

Previous work uncovered concerns about the rise of consumer-oriented thermal cameras in terms of misuse and misinterpretation [23,24]. For example, in [23], while professional energy auditors' emphasized the value of thermograms in explaining otherwise invisible phenomenon to homeowners they emphasized that it required "skill and expertise" to correctly interpret. Indeed, in our study we found misuses of thermal cameras (*e.g.,* attempting to observe gases) as well as misinterpretations (*e.g.,* using surface temperature as a direct proxy for air temperature). However, these were less frequent than expected—comprising only 5.3% of our dataset. Moreover, we found that some content creators demonstrated a sophisticated level of understanding (*e.g.*, describing thermal reflectivity of a material or the need to calibrate for emissivity). Nevertheless, overcoming these challenges will be critical to helping users avoid the negative consequences of incorrectly interpreting thermal data as there can be tangible costs to such misinterpretations. For example, a misdiagnosis could lead to investing in needless repairs or, conversely, a missed opportunity for improvement in the building and electronics contexts.

Anticipating a Shift in User-base and Understanding

Admittedly, the users in our dataset likely represent the most interested non-professional thermal camera users, who may be more confident in their activities and interpretations than the general population (*e.g.,* novice thermographers not on YouTube). As the user population shifts from those having made a conscientious decision to purchase thermal cameras to a population with a less purposeful acquisition (*e.g.,* smartphones that include thermal sensors [38]) users may have a less vested interest in learning about the technological constraints of thermal cameras. Such non-expert, non-invested users may be more likely to encounter challenges and misconceptions. To support a future where novices have easier access to thermal camera technology, future applications and services should consider how to support users in learning thermography best practices.

Implications for Design

To better support non-professional thermal camera users in collecting and analyzing thermography data, we offer several implications for the design of future thermographic systems and tools that will address the challenges identified in our findings and in prior work.

Provide Contextually Relevant Information. Future applications should suggest appropriate uses of thermography within different contexts (*e.g.,* the potential value of time lapse video in assessing heat and power management in electronics) and offer information related to common interests (*e.g.,* why the surface of hot liquids such as coffee display patterns). Such dynamic context awareness can improve thermographic systems [2] and help users learn to use the technology properly. While the YouTube community supports this informally through online videos, we suggest integrating this information directly in the thermal user interface via interactive onboarding within the mobile applications that smartphone camera attachments (and integrated cameras) rely on.

Encourage Exploration. While thermal camera users initially purchased devices for one or two purposeful activities (*e.g.*, wildlife tracking, building thermography), users often ended up exploring a wider range of uses out of curiosity. Encouraging exploration would empower users to take full advantage of this sensing technology in diverse ways provided data is correctly collected. This practice could have further benefits, such as contributing to citizen science efforts by leveraging interest in wildlife tracking to simultaneously creating new sources of data for environmental and conservation purposes (*e.g.,* locating bird nesting sites [13], monitoring honeybee colonies [17]).

Anticipate and Prevent Misconceptions. Advances in integrating thermographic data with machine learning and computer vision technology [10,39] could help combat misconceptions, misinformation, and misuse by aiding users in analysis/interpretation and making the limitations of thermography more understandable. For example, automatically detecting the presence of glass windows or ceramic bathroom tiles in an image could bring up information about the reflectivity of these materials. To accomplish this goal, it will be important to continue studying thermography users and communities to identify common pitfalls and determine when *in-situ* assistance is applicable and desired.

Enable Social Supports. Previous work suggested that novice thermal camera users might benefit from having social support communities available to them [24]. This work provides continued evidence that thermography users enjoy and learn from social interactions, here, in an online community. As with previous work emphasizing the impact of social supports in online communities [28,30], our work suggests that providing online social supports for thermal camera users could promote users' enjoyment, technical understanding, and proper use.

Reflections on the Dataset Generation Method

As a secondary contribution of this work, we extend the methods used in [3,4,6,14,26] by incorporating machine learning and information retrieval algorithms into our data search process. This hybrid manual+computational approach, further detailed and evaluated in [22], provided a relatively fast and robust way to sample data, codified our process of filtering YouTube data, and allowed us to predict the relevance of videos in our dataset *a priori*. Still, there is room for improvement. Our automated techniques did not analyze the video content itself (*e.g.,* transcripts or video stills) and only 67.5% of videos in our dataset were identified as in-domain and on-topic for "everyday use". However, the 1,092 videos retrieved using our initial keywords, which reflects the more common methodological practice, only contained 187 "everyday use" videos. We therefore were able to increase our relevant dataset size by over three-fold using the hybrid method. Despite this success, it is likely that higher quality training labels combined with additional data from the video content would improve performance. Future work should explore expanding this approach by incorporating new computational methods to analyze video content and examine additional social media data (*e.g.,* recommended videos, relevant channels).

Limitations

In addition to previously described limitations, each method in our mixed-methods study—video content analysis, comment analysis, and the online survey—has limitations. The video analysis is limited to the YouTube community and those users with the ability to upload videos. Survey findings are limited by self-selection bias, unverifiable participant claims (*e.g.,* energy savings), and gender skew (all respondents were male; a similar male prevalence exists in prior work [23]). Finally, within the YouTube comment analysis, answer accuracy was only evaluated in relation to misconceptions or misinformation.

CONCLUSION

This paper presents the first qualitative, human-centered inquiry into "in the wild" use of thermal cameras by non-professionals. Using a mixed-method approach, we analyzed 1000 YouTube videos, analyzed the question and answer discourses within video comments, and further surveyed the content creators to characterize end user-behavior and motivations. We learned that non-professional users apply thermography widely: activities ranged from investigating domestic objects to focused investigations of buildings and electronics. Contrary to previous work, we found that users investigated technological limitations and, largely correctly interpreted their data. Our characterization of novice users and common thermographic use cases extends discussions surrounding novices uses and the challenges novices encounter which have implications for the design of future thermographic systems and tools.

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