RASSAR: Room Accessibility and Safety Scanning in Augmented Reality

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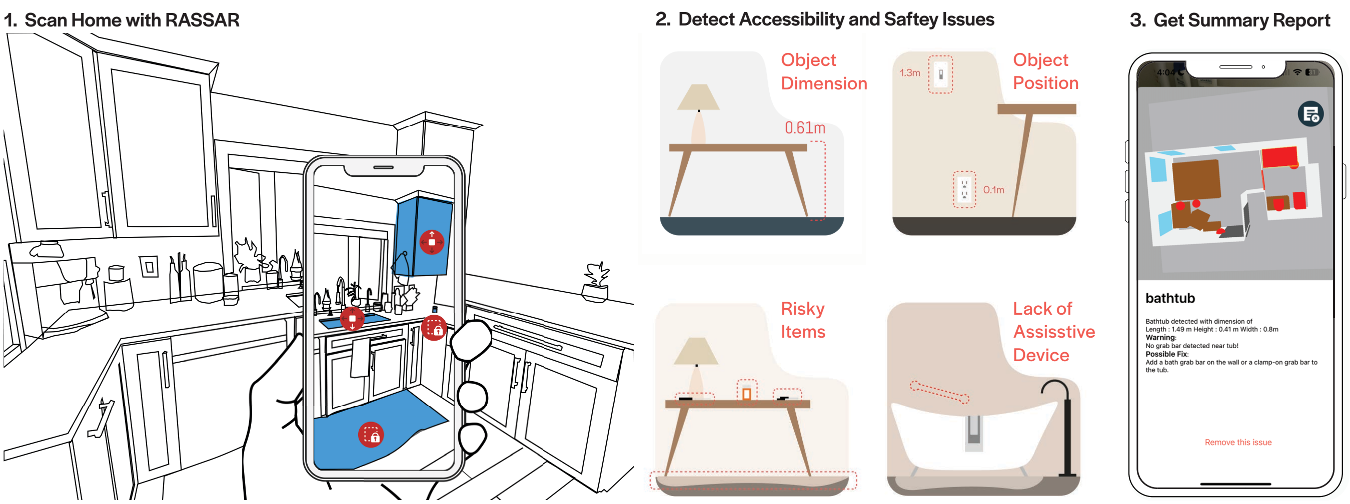

Figure 1: RASSAR is a mobile AR application for semi-automatically *identifying*, *localizing*, and *visualizing* indoor accessibility and safety issues. (1) RASSAR scans home spaces and detects potential issues in real time using LiDAR and computer vision. (2) RASSAR currently supports four classes of issues, including inaccessible *object dimensions* such as a high/low table top or the presence of risky/dangerous items such as scissors. (3) After a scan, RASSAR generates an interactive summary of identified problems with a 3D reconstructed model.

ABSTRACT

The safety and accessibility of our homes is critical to quality of life and evolves as we age, become ill, host guests, or experience life events such as having children. Researchers and health professionals have created assessment instruments such as checklists that enable homeowners and trained experts to identify and mitigate safety and access issues. With advances in computer vision, augmented reality (AR), and mobile sensors, new approaches are now possible. We introduce *RASSAR*, a mobile AR application for semi-automatically *identifying*, *localizing*, and *visualizing* indoor accessibility and safety issues such as an inaccessible table height or unsafe loose rugs using LiDAR and real-time computer vision. We present findings from three studies: a formative study with 18 participants across five stakeholder groups to inform the design of RASSAR, a technical performance evaluation across ten homes demonstrating state-of-the-art performance, and a user study with six stakeholders. We close with a discussion of future AI-based indoor accessibility assessment tools, RASSAR's extensibility, and key application scenarios.

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CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing design and evaluation methods**; **Accessibility systems and tools**.

KEYWORDS

Accessibility, Computer Vision, Augmented Reality, Indoor Accessibility Auditing, Object Detection

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1 INTRODUCTION

Safe and accessible living spaces are a fundamental human right [43]. Yet, inaccessible housing remains prevalent throughout the world. In the US, for example, 90% of housing units are inaccessible to people with disabilities [53, 54]. In the UK, 98% of newly built private homes are inaccessible to wheelchair users [28]. To improve the safety and accessibility of domestic spaces, researchers and health professionals have created pre-formatted checklists that help residents and trained professionals audit and renovate indoor spaces [11, 19, 30, 55]. For example, the *Home Safety Self-Assessment Tool* (HSSAT) [24, 60] includes a checklist for issues such as uneven flooring, cluttered areas, slippery throw rugs, and inaccessible light switches across nine home areas (*e.g.,* kitchens, bathrooms, and bedrooms). Others have explored remote assessment methods via teleconferencing and video cameras [46, 48].

With advances in computer vision (CV), augmented reality (AR), and mobile sensors, new ways to assess indoor accessibility and safety are now possible. For example, emerging smartphones contain built-in *Light Detection and Ranging* (LiDAR) sensors [4], which can reconstruct indoor spaces in real-time with high precision [15], new CV models like *YOLO* [32] are capable of high recognition rates across object types, and smartphones contain powerful computational units for onboard processing. Leveraging these advances, we created *RASSAR—Room Accessibility and Safety Scanning in Augmented Reality*—a custom mobile AR application for semi-automatically *identifying*, *localizing*, and *visualizing* indoor accessibility and safety issues using LiDAR and real-time computer vision (Figure 1). With RASSAR, a user scans an indoor space with their phone; the tool constructs a real-time parametric model of the 3D scene, attempts to identify and classify known accessibility and safety issues, and visualizes potential problems in AR overlays. Throughout the scan, users can confirm/delete automatic detections or select them to view more information (see Figure 5). After scan completion, RASSAR shows an interactive 3D room reconstruction with a summary of findings (Figure 1 and Figure 6). Additionally, to assist blind or low vision users, we designed RASSAR to support VoiceOver and provide custom audio assistance about the scanning process (*e.g.,* verbalizations of detected items).

To develop RASSAR, we conducted a three-stage iterative design process. First, informed by prior work [1, 24, 26, 60], we built a *rapid technical prototype* to demonstrate feasibility and examine initial audit possibilities. Second, using this prototype as a design probe [16, 22, 31, 49], we conducted a *formative study* with 18 participants across five stakeholder groups: wheelchair users, blind and low-vision participants, families with young children, caregivers, and occupational therapists. We showed working videos of RASSAR auditing an apartment, solicited feedback on new interface mock-ups, and engaged participants in co-brainstorming new features. Study findings reveal common challenges in home accessibility and auditing processes that RASSAR can potentially alleviate, along with suggested improvements to its rubrics and UI. Third, we *built the current RASSAR system* with improved detection performance, user interaction, and interface design and performed two additional studies: a technical performance evaluation (Study 2) and a user study (Study 3) with six participants again drawn from our five stakeholder groups.

As emphasized in literature [55] and further affirmed by our formative study, home audit tools must be adaptable to address individual needs and differences across community groups. To address this challenge, RASSAR introduces a custom and fully extensible JSON format to encode specific accessibility/safety issues into its audit engine. Currently, RASSAR supports 20 issues across four problem categories: *object dimension* (*e.g.,* table too low), *position* (*e.g.,* light switch too high), *risky items* (*e.g.,* throw rug), and *lack of assistive device* (*e.g.,* no grab bar near toilet). New issues can be added via a text editor with JSON. In the future, such additions could be made via an envisioned authoring tool.

To evaluate RASSAR's performance and usability as well as its effectiveness in real-world settings, we conducted the aforementioned technical evaluation and user study. In the technical evaluation, the first author visited ten homes of varying sizes and layouts, conducting both a manual baseline audit and a RASSAR scan for comparison. Each RASSAR scan was repeated three times to examine consistency. The user study followed a similar procedure; however, in this case, the participants themselves conducted RASSAR scans independently. We then interviewed participants about their experience to gather qualitative insights. We found an average scan precision/recall of 0.86/0.83 when conducted by the researcher and 0.79/0.73 when scanned by participants. Our findings show that RASSAR is not only usable and useful but also significantly increases efficiency, achieving an auditing speed 3.5x faster than manual auditing. As P4, a wheelchair user, said: "*RASSAR is easy to use and was pretty accurate in terms of ADA*".

In summary, our contributions include: (1) formative findings from five stakeholder groups about their current indoor safety/accessibility audit practices, their methods for reconfiguring spaces to fit their needs, and reactions to future indoor auditing tools using advanced sensing; (2) the design and implementation of RASSAR, a novel AR-based tool for semi-automatically detecting safety/accessibility issues in indoor spaces using LiDAR and real-time CV; (3) findings from a technical performance evaluation and a follow-up user study demonstrating effectiveness and potential applications of RASSAR. As secondary contributions, we introduce an extensible JSON format for specifying indoor safety/access issues and provide a specified object detection model and its training dataset. We have also open sourced RASSAR along with the detection model and its training dataset at https://github.com/makeabilitylab/RASSAR.

Our work aims to transform how people examine and configure indoor spaces to improve accessibility/safety. We envision RASSAR as a versatile tool to aid builders in considering and validating the safety and accessibility of new construction, residents in planning renovations or updating their homes due to life changes (*e.g.,* illness, birth), rental agencies like Airbnb in vetting and validating the accessibility and safety of rental spaces, and occupational therapists in assisting residents as they comprehensively assess and identify safety/access issues during home visits.

2 RELATED WORK

We contextualize our work within the home accessibility and safety auditing literature as well as automatic accessibility auditing and indoor scanning and reconstruction using LiDAR.

2.1 Home Accessibility/Safety Auditing Methods

To improve the accessibility and safety of home spaces and improve the person-environment 'fit' [37], a thorough assessment for potential risks based on residents' needs is required. This assessment—called *home accessibility and safety auditing*—traditionally involved professional occupational therapists (OTs) with experience and insights about the challenges and remedies for home accessibility issues [30]. To help OTs conduct standardized evaluations, checklists like *WeHSA* [11], *Housing Enabler* [30], *SAFER-Home* [10], and *HEAVI* [57] were developed and deployed. These checklists contain potentially hundreds of potential risks for OT's to monitor during home visits (*e.g.,* uneven steps, bed too high, slippery floors).

However, healthcare system barriers like limited funding and lengthy insurance approval processes can impede on-site OT interventions [46]. In this case, occupant-oriented checklists, like the well-known HSSAT [24, 60], help people audit home spaces by themselves. Compared to the checklists for OTs, these consumer checklists [18, 20, 21, 25] are designed to be more community/demographic specific (*e.g.,* for older adults only), pictorial, and subjective. They usually contain detailed descriptions of potential risks and ways to overcome them.

Besides checklists, which aim to discover problems in existing spaces, legal regulations also address home space accessibility. For example, the *Fair Housing Act (FHA) Design Manual* [26] and *the Americans with Disabilities Act (ADA) Design Guidelines*[1] present detailed design guidelines for home design and construction. Unlike home accessibility checklists, these guidelines are more specific about measurements of dimension and positioning of housing components, but they are less specific about specific communities/demographics and usually not as close a fit for personal needs.

In general, current home accessibility assessment practices require either manual measurements and ongoing checking or the participation of professional OTs. Such practices continue to pose barriers to home assessments due to residents' abilities, financial budget, and motivational factors. We address this gap by developing and evaluating RASSAR to enable reliable, fast, and always-available home auditing using smartphones, reducing the effort and potential resources needed to accomplish this vital task.

2.2 Automatic Evaluation of Real-world Safety/Accessibility

There has been a growing interest in using the latest sensing and computing technologies, such as crowdsourcing, indoor reconstruction, and computer vision, to improve safety and accessibility of the built environment. However, we observe an imbalanced focus on outdoor *vs.* indoor spaces. One outdoor example is Project Sidewalk [50, 52, 63], which crowdsources annotations on street view data and uses deep learning models (such as ResNet) to detect target objects like curb ramps and inaccessible sidewalk conditions. Other works apply similar pipelines to pedestrian facilities [36, 39]and street bikeability [29]. Most relevant to our work is Ayala-Alfaro *et al.*'s research on indoor obstacle identification [7]. While similar, our work provides user participation and verification, a wider range of accessibility issues, as well as customizability for people with different accessibility needs.

In addition to image-based methods, researchers are using agent-based modeling [17], graph-based methods [12, 23] and point cloud data [2, 7, 8, 51] to evaluate accessibility in built environments. For example, Fu *et al.* [17] place virtual human agents into given 3D indoor scenes to interact with indoor objects in order to evaluate functional accessibility. Balado *et al.* [8] uses a MLS (Mobile Laser Scanner) to scan the facade of buildings and segment the point cloud data to detect potential accessibility issues at building entrances. Compared to image-based methods, these works are more difficult to apply at large scale due to the cost of specialized hardware and the complexity of data collection and analysis.

In general, existing work requires massive amounts of data collection or specialized hardware to generate identified accessibility issues. In contrast, RASSAR empowers individuals to identify home accessibility issues tailored to their unique requirements using their smartphones. Our distinctive approach actively engages users in the AR-based scanning and evaluation processes.

2.3 LiDAR-based Indoor Scanning & Reconstruction

In recent years, many mobile device manufacturers such as Apple, Samsung, and Huawei, have incorporated LiDAR sensors into smartphones. Apple's iPhone 12 Pro, for example, was released in 2020 [4] and provides both hardware and software support for users to conduct scans and reconstruct indoor spaces. Although smartphone-based LiDAR capabilities cannot match professional devices, researcher evaluations demonstrate ample precision [15, 38, 62]. In May 2022, Apple released another indoor reconstruction API called RoomPlan [5], which uses the camera, LiDAR sensor, and deep learning models to create real-time parameterized indoor models. This API simplifies the indoor reconstruction process and expands potential application scenarios by generating 3D models with dimension, position, and category.

Although 3D reconstruction technology is rapidly advancing, two important gaps remain: the lack of focus on accessibility and safety in indoor reconstruction, and the inability to detect and locate accessibility-related objects in indoor spaces. RASSAR addresses these gaps by combining the mobile-based indoor scanning and reconstruction pipeline with accessibility rubrics and offering a custom, accessibility-focused object detection model.

3 DESIGN PROCESS

To design RASSAR, we conducted a three-stage iterative design process. We first built an *initial technical prototype* to demonstrate feasibility. Then, we used our initial prototype as a design probe to conduct a *formative user study* with five key stakeholder groups (Study 1). Finally, based on formative study findings, we built the *current RASSAR system* with improved detection performance, rubric formation, user interaction, and interface design—and then performed both a technical evaluation (Study 2) and a user study (Study 3).

3.1 Technical Prototype

Informed by prior work in home accessibility assessment [8, 17] and indoor reconstruction techniques [5, 64], we built a rapid technical prototype on an iPhone 13 Pro Max using *Apple's RoomPlan API* [5]. The prototype included three primary features: (1) a reconstruction of indoor spaces with accessibility-related items, (2) the detection of accessibility and safety issues in indoor scenes, and (3) an AR-based visualization of and interaction with detected accessibility and safety issues. We used this prototype to conduct controlled experiments of a single apartment to demonstrate technical feasibility and determine ideal scan conditions, such as varying levels of room tidiness, lighting, and moving speeds [56].

Our initial findings suggest that scanning must be conducted at moderate speed (moving at 0.5 meters/sec) while keeping the room tidy and well-lit. Under such conditions, the technical prototype's detection recall reached 90%. The experiment also revealed deficiencies in object detection performance and UI limitations, which we later improved in the final RASSAR system (Section 4).

3.2 Study 1: Formative Study

To examine the potential of semi-automatic accessibility and safety scanning with mobile phones and to solicit feedback of our initial technical prototype, we conducted a three-part formative user study with 18 participants drawn from five communities: wheelchair users (*N*=8), families with young children (*N*=3), people who are blind or low vision (*N*=4), older adults (*N*=6, including caregivers), and occupational therapists (*N*=3); see Table 1.

Table 1: Our formative study included 18 participants. *PID* stands for Participant Index. *Older Adults* refers to those aged 65 and over. *Children* to those families with children between 0 and 3 years old. *BLV* to people who are blind or low vision. *OT* to occupational therapists. *CG* to caregiver. As can be observed, identities/roles are not mutually exclusive.

PID	Wheelchair User	Older Adults	Children	BLV	OT
P1	✓				
P2	✓				
P3	✓				
P4	✓				
P5	✓				
P6	✓				
P7			CG		
P8	✓	✓			
P9		CG	CG		
P10	✓	✓			
P11					✓
P12					✓
P13		✓		✓	
P14		✓		✓	
P15		✓		✓	
P16			CG		
P17					✓
P18				✓	

3.2.1 Participants. Participants were recruited via email, advertisements to accessibility organizations, and social media as well as through snowball sampling. Before participating, all individuals filled out a screener on demographics and relationship(s) to our target communities. To ensure a diverse sample, we recruited at least three individuals from each community who were either self-identified members or caregivers.

3.2.2 Procedure. We conducted a three-part, qualitative study. Part 1 addressed current practices, and Parts 2 and 3 focused on our RASSAR design probe. Specifically, in Part 1, we asked participants about their indoor accessibility and safety needs, their current practices for assessing those needs, and challenges therein. For Part 2, we showed participants videos of RASSAR scanning an apartment and solicited suggestions, concerns, and expected usage scenarios in their own lives. Finally, in Part 3, we showed RASSAR UI mockups as design probes and asked participants for preferences: how to encode new accessibility/safety issues into RASSAR (*e.g.*, rubric customization), how to guide the user-conducted scan, and how to provide feedback for scan results and errors. Sessions lasted between 40-70 minutes (*Avg*=52 mins), and all but one was conducted over Zoom. The lead author conducted all 18 sessions. For reference, we include the full interview protocol and design probe in the supplementary files.

3.2.3 Data and analysis. We audio and video transcribed all sessions via Rev [47]. For analysis, we conducted reflexive thematic coding [9]. The first author, who also conducted the interviews, reviewed all transcripts to develop an initial codebook. The first four authors then discussed the initial codebook, iteratively resolved disagreements and developed a full version of the codebook collaboratively. The first author then applied the finalized codebook to all transcripts. After coding ended, the first four authors met and discussed general themes and findings.

3.2.4 Findings. We highlight four key findings below related to indoor accessibility and safety needs, current practices and challenges in assessing indoor accessibility and safety, reactions to *RASSAR*, and our design probe results.

Overall reactions to RASSAR. Most participants (*N*=16) held favorable opinions about the RASSAR prototype due to its measurement and documentation features, its ability to help prepare a home for visitors with accessibility needs, and its ability to customize accessibility issues. The two participants who held unfavorable or neutral opinions stated, "*I don't see the point since I can do these screenings by myself*" and "*I don't know.*"

Participants described a variety of usage scenarios for RASSAR. Six participants mentioned how RASSAR could help people gain knowledge of physical spaces before they actually visit them. For example, P18 (BLV) said, *"I think it could really help people have more confidence when they go into a room that they're not familiar with or a new space."* Another commonly raised use-case was facilitating renovation or real-estate viewings; for example, P4 (wheelchair user) said, "*I could even see this as being incredibly helpful to send to contractors and architects and designers.*" Finally, participants were excited about ways RASSAR could facilitate accommodation during travel, since hotel or Airbnb managers can better communicate accessibility situations with RASSAR scan results.

People's unique indoor accessibility needs. Our participants flagged common sources of indoor safety and accessibility issues, such as stairs (*N*=14), doors (*N*=9), and floors (*N*=9), which also commonly appear in accessibility checklists [24, 59, 60]. However, we also found key differences in concerns across communities. For example, no wheelchair user mentioned concern about hazardous items like sharp furniture corners or knives, while all other communities (BLV *N*=3, older adults *N*=4, children *N*=2, OT *N*=1) stressed it in interviews. This highlights the need for RASSAR to be customizable to address different abilities and needs.

Current practices and challenges. None of our participants with accessibility needs previously chose to use accessibility checklists when auditing indoor spaces. They instead relied on their own experiences and formed methods through practice. The most commonly used methods were exploring the space (*N*=6), creating mind maps of potential issues (*N*=5), and asking questions about the space (*N*=4). Caregivers typically put themselves in care receivers' shoes (*N*=2) to better identify potential issues. Current practices also posed inherent challenges, including other people's limited understanding of accessibility (*N*=3) and social awkwardness (*N*=3).

For example, P10 said, "*People mean well, they really do. [But] until you actually have to live it or be exposed to it on a routine basis, you just really don't understand [our accessibility challenges].*" Similarly, P6 said, "*The main challenge is explaining to people how to look at it from my perspective.*" In this case, audits should be conducted on-site by individuals with accessibility needs themselves for reliability, requiring extra time or money to resolve or circumvent issues. P8 recalled an instance of calling a restaurant to confirm accessibility, only to find it inaccessible upon arrival, forcing her to choose a nearby alternative. We maintain that these challenges can be mitigated by indoor auditing methods such as RASSAR, which provides a holistic digital scan of space that can be evaluated remotely based on general or personal requirements.

Design improvements for RASSAR rubrics and UI. We presented participants with a list of accessibility and safety issues derived from literature to solicit feedback. Most participants were satisfied, while some suggested additions. Based on feedback, we modified and finalized RASSAR's auditing rubrics (*e.g.,* added new issues like bed height). We also provided UI mockups to solicit participants' preferences about RASSAR's scan experience (Figure 2). Participants preferred having text hints (*N*=15) and mini-maps (*N*=11) for scanning support, an interactive rich text pop-up layer (*N*=13) for detected issue visualization, an interactive 3D model (*N*=9), and a list of issues to review (*N*=10) in a post-scan summary. As for methods of error reporting, most participants (*N*=15) preferred that the system learn their needs over time.

4 THE RASSAR SYSTEM

Informed by our rapid prototype and formative study findings, we created a revised RASSAR system (Figure 3), which uses LiDAR and real-time CV to perform a parametric reconstruction of indoor spaces, automatically identify safety and accessibility problem using a custom JSON rubric, and visualize issues both in AR and via an interactive 3D summary view.

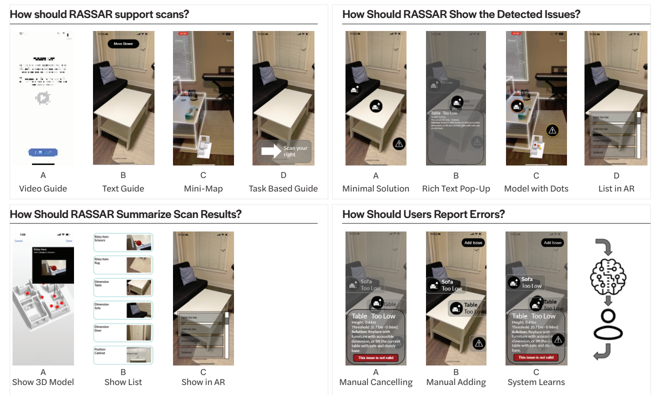

Figure 2: Design probes for RASSAR's interaction and interface design. For each question, we provide three or four options as interface mock-ups.

The new prototype includes four key enhancements: (1) *Improved feedback:* all detected accessibility and safety issues are visualized in real time with multiple UIs, including a pop-up icon in the AR interface, descriptive layers, and post-hoc summarization in the 3D model. This empowers users to actively engage with the system to explore, refine, and summarize scan outcomes. (2) *Reduced scanning effort:* RASSAR users can learn to scan rooms with both textual and mini-map hints, and the app is designed to help users scan spaces without having to move close to potential objects of interest, thereby reducing scanning effort. (3) *Customizability:* RASSAR users can tailor the scanning process by selecting different accessibility communities to filter detection rubrics. They can also manually remove detected issues that fail to match their specific needs. (4) *BLV support:* To assist BLV users, each of the primary user interactions—selecting target communities, scanning, object identification, and summary of results—are supported by real-time audio feedback. All user interface components, such as buttons and text labels, are compatible with VoiceOver. Below, we describe RASSAR's scanning, detection, and visualization process.

4.1 Scan and Reconstruct Home Space

In Step 1 of RASSAR's technical pipeline, we reconstruct a scanned home space into a parametric 3D model that includes object category, dimension, and position information. To create a reconstruction with access/safety information about both *macro* objects (*e.g.,* furniture) and *micro* objects (*e.g.,* electric sockets), we combine *Apple's RoomPlan API* [5] and a customized *YOLOV5* model [32].

4.1.1 Parametric eeconstruction of major indoor components. The RoomPlan API is the backbone of our indoor reconstruction process. RoomPlan, which relies on both RGB camera and LiDAR sensor data, provides real-time spatial and dimension information for major indoor components. Currently, RoomPlan detects the following object categories: *bathtub*, *door*, *opening*, *wall*, *window*, *bed*, *chair*, *sink*, *sofa*, *stairs*, *storage*, *table*, *television*, and *toilet*. However, this

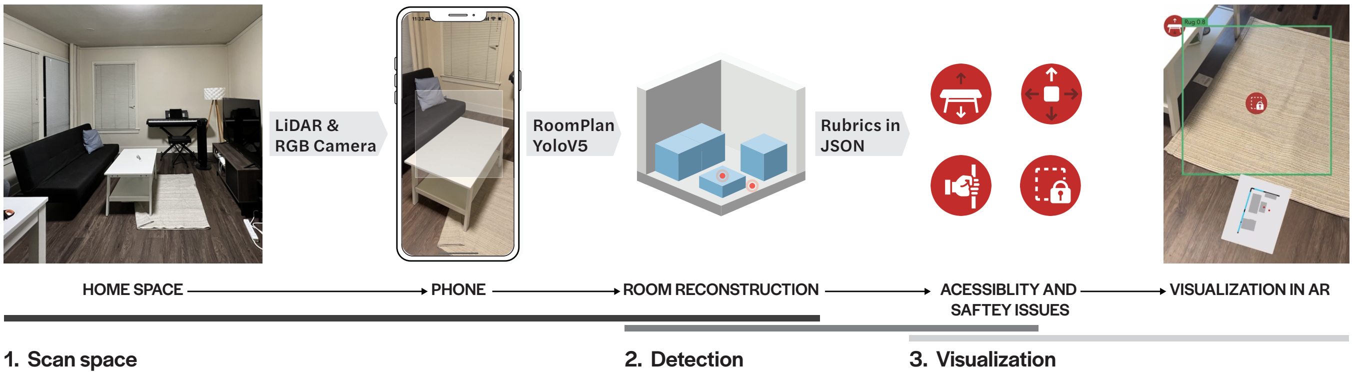

Figure 3: RASSAR system overview. RASSAR (1) scans and reconstructs a home space, (2) detects accessibility and safety issues in the space, and (3) visualizes real-time results in AR.

reconstruction is incomplete; it includes only walls, doors and furniture but neglects smaller objects that could also pose accessibility and safety challenges.

4.1.2 Object detection for smaller indoor objects. Based on our literature review, we identified many issues related to smaller objects, such as *grab bars*, *electric sockets*, and *sharp objects*. Since no existing pre-trained model is tailored for accessibility-related indoor objects, we trained our own object detection model to complement our room reconstruction pipeline. Informed by [1, 24, 26, 33, 41, 60], we selected nine initial categories of smaller indoor items that are common problems and collected a customized dataset with 2533 images and 3943 annotations (Table 2). About one third of these images come from the *Open Images* dataset [35], while the remainder comes from *Microsoft's Bing* [40]. The first author manually annotated annotated all instances of the nine object categories (Table 2) with bounding boxes.

Using the dataset, we trained a state-of-the-art computer vision model, YOLOV5[32]. We specifically selected *YOLOV5-m* (41 MB) due to its fast detection speed (224ms inference time with CPU [61]) and good performance on the baseline COCO dataset (0.63 for mAP@0.5[1]). In offline experiments, we found that a larger model would slightly increase performance (0.66 for mAP@0.5) but almost double detection speed (430ms). We trained our model on an NVIDIA GTX 3080 and Ubuntu 20.04.2 LTS using 900 epochs. After obtaining the best weights, we converted them into the CoreML format (.mlmodel) [3] by adding a non-maximum suppression layer [32]. We randomly sampled our dataset into training, validation, and test sets containing 70%, 15%, and 15% of the data, respectively. The model performance is shown in Table 3. To facilitate open science, we have open sourced the annotated dataset [2].

During the scanning process, the custom YOLOV5 model runs continuously on the camera feed to detect the nine accessibility-related objects in the scanned space. Since YOLO detection results are 2D bounding boxes on images instead of 3D coordinates in a room, we perform raycasting [6] to convert the 2D location from the center of the YOLO bounding box into 3D coordinates in physical space. To improve accuracy and reduce noise and outliers, we smooth out the raycasting results by averaging across multiple frames and setting up filtering thresholds. For a YOLO-detected

Table 2: The number of images and annotations for training RASSAR's customized YOLO model. Some images contained multiple objects, which is why the annotation count exceeds the image count.

Object	Images	Annotations
Door handle	370	530
Electric socket	181	370
Grab Bar	395	503
Knife	451	622
Medication	325	688
Rug	377	470
Scissors	226	270
Smoke alarm	176	191
Light switch	138	299
Total	**2533**	**3943**

Table 3: Performance of our trained model for each object category. mAP is mean Average Precision, and 0.5 is a common threshold to determine the effective intersection over union (IoU).

Class	Target	Precision	Recall	mAP@0.5
All	587	0.744	0.865	0.869
Door Handle	66	0.601	0.803	0.746
Electric Socket	30	0.719	0.867	0.877
Grab Bar	104	0.777	0.952	0.972
Knife	93	0.682	0.71	0.756
Medication	113	0.831	0.938	0.944
Rug	60	0.965	0.983	0.994
Scissors	60	0.775	0.85	0.887
Smoke Alarm	29	0.765	0.931	0.873
Switch	32	0.579	0.75	0.767

[1] mAP@0.5 represents the *Mean Average Precision* at an *Intersection over Union* (IoU) threshold of 0.5
[2] https://github.com/makeabilitylab/RASSAR

object to be considered valid, it needs five raycasting results with location offset of fewer than 0.3 meters and YOLO detection confidence scores greater than 0.65.

Combining the results of RoomPlan and YOLOV5, RASSAR produces a real-time indoor reconstruction that includes category, dimension and position information of both larger barriers and many smaller indoor objects. This room reconstruction provides a solid basis for accessibility and safety auditing.

4.2 Detection of Accessibility and Safety Issues

In Step 2 of RASSAR's pipeline, we filter and identify relevant accessibility and safety issues based on the selected stakeholder group(s) and a customizable rubric.

4.2.1 Rubric formation. RASSAR's auditing rubric is drawn from *ADA Design Guidelines* [1], the *Home Safety Self Assessment Tool* (HSSAT) [24, 60], the *US Fair Housing Act Design Manual* [26, 54], and other sources [44, 58]. Creating the default rubrics for each stakeholder group was iterative and additionally informed by Study 1. The final rubrics include 20 issues across four categories (Figure 1.2, Figure 4): *object dimension* (*e.g.,* high table height), *object position* (*e.g.,* out-of-reach light switch), *risky items* (*e.g.,* presence of a sharp object like scissors), and *lack of assistive items* (*e.g.,* missing bathtub grab bars). For more details, see Appendix B. When RASSAR starts, users can select one or more target communities, which will load the relevant rubric(s).

4.2.2 JSON-encoded rubrics. To facilitate both automated screening of room reconstruction and individual customization, we transformed our original text-based rubrics into *JavaScript Object Notation* (JSON) format. Each JSON-formatted rubric encompasses essential details, such as the target object category (*e.g.*, table), its relevant user community (*e.g.*, wheelchair users), the dependent other object when rubric involve multiple objects (*e.g.*, tub for the issue of *No Grab Bar Near Tub*), and the violation criteria (*e.g.*, dimensions less than 68 cm, and relative distance more than 70 cm away). Moreover, we enriched these JSON files with supplementary information, including warning messages, issue descriptions, suggestions, and information sources. This additional context aids users in comprehending detected issues and assists in the removal of invalid or irrelevant results. See Appendix A for an example.

4.3 Visualization of scans

Finally, in Step 3, RASSAR provides a real-time 3D reconstruction to aid scanning, a visualization of identified issues in AR, and a post-hoc summary of scan results.

4.3.1 Facilitating user scanning. The RASSAR interface employs several user feedback methods to facilitate scanning. First, real-time room reconstruction progress is visually represented through a dynamic mini-map (Figure 5d). This mini-map adapts to the user's orientation and shows real-time reconstruction progress with distinct visual cues (*e.g.,* black lines signify walls, yellow lines denote doors, and the orange triangle indicates the user's current position and direction). Second, to enhance the capture of smaller indoor objects from a distance, RASSAR optimizes its camera feed by utilizing only the central part of the screen as input to the YOLO model. Users are guided by a subtle, dimmed white box (Figure 5b). Third, all object detection results are presented in YOLO-style bounding boxes (Figure 5c). Finally, users can also enable audio feedback during the scanning process, which verbally guides the scan with instructions such as "*Please point camera at top and bottom of wall to initialize*", "*Please slow down*", and "*Please step away from wall.*" All major indoor objects, such as doors, windows, tables, and sofas, are read out when detected.

4.3.2 AR visualization of detected issues. We also overlay detections in real-time using AR. The four classes of accessibility issues (*object dimension*, *object position*, *risky item*, and *lack of assistive item*, see Figure 4) are encoded and shown via four corresponding pop-up icons. Icons are clickable to inspect detailed information (Figure 5.2) and verify if the issue is valid. If not, the user can remove the issue (Figure 5e). With audio support enabled, RASSAR also verbalizes when an accessibility or safety issue is detected, such as "*Too narrow door opening is detected!*", "*The bed is too high!*", and "*No grab bar detected near toilet!*"

4.3.3 Post-scan interactive 3D summary. After a scan, RASSAR provides a brief summary of detected issues, including issue counts and their category—which can be read out with VoiceOver RASSAR then shows an interactive 3D model of results where indoor components and objects are represented as geometries and detected issues are shown in red. The user can pan, zoom and move the 3D model to inspect more closely or tap on any object to see more details. The lower half of the UI shows details about user-selected objects, including object category and dimension. The user can also delete detected issues or export all scan results into a JSON file.

5 STUDY 2: TECHNICAL EVALUATION

Prior work in automatic accessibility auditing typically includes technical performance evaluation "case studies" in 3-4 real-world environments [8, 13, 14]. Expanding on this approach, we performed technical evaluations of RASSAR in 10 home spaces, including seven apartments and three houses of varying sizes and layouts (Table 4). The first author, an experienced accessibility researcher and expert RASSAR tool user, conducted all scans.

5.1 Experiment Procedure

For each indoor space, we performed a three-step process. First, we conducted a *manual audit* to identify any existing accessibility and safety issues using RASSAR's accessibility rubrics (Appendix B). We inspected and measured each indoor space, used the rubric for assessment, and took additional notes about found issues[3]. Second, we *scanned each space with RASSAR*, which we recorded and exported to JSON format. Finally, we *compared the scan results* with the manual audit data. We repeated the last two steps three times, resulting in 30 RASSAR scans across the ten indoor spaces.

5.2 Evaluation Metrics

To evaluate RASSAR, we used three primary evaluation measures: *detection performance*, *scanning consistency*, and *scanning time*.

[3]We excluded the *'Knob Height'* issue from this study to avoid imbalance of issues in the manual inspection results.

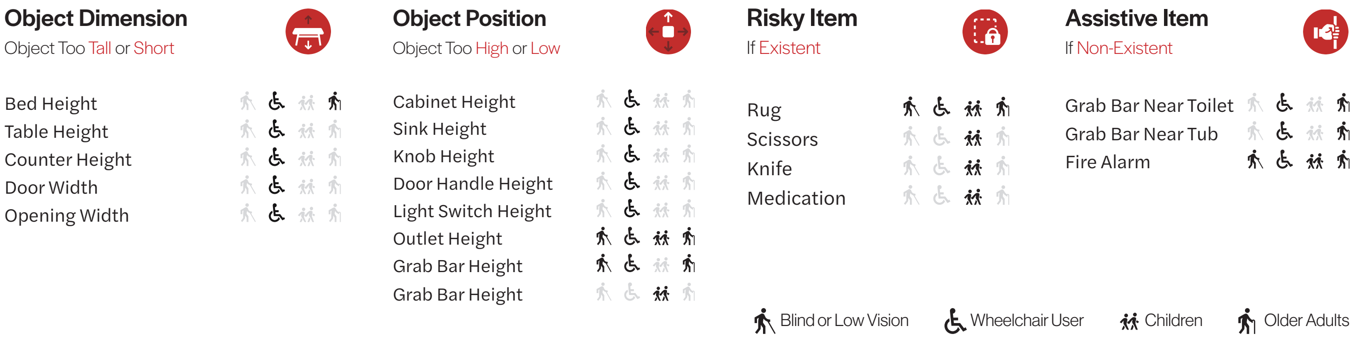

Figure 4: Informed by literature and our formative study, RASSAR can detect 20 types of accessibility and safety issues across four categories: *object dimension, object position, risky item,* and *assistive item.* Each issue has relevance to specific accessibility communities, marked with black icons. We acknowledge that safety/accessibility issues can be fluid marked not just by (dis)ability but fatigue, time-of-day, *etc.* and that individuals may not map exactly to these categories. Our custom JSON-based rubric could allow for precise individual specification in the future (*e.g.,* with a custom authoring interface.

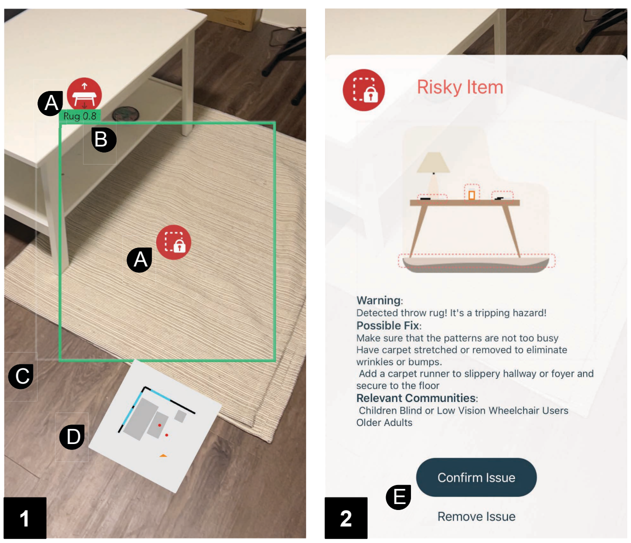

Figure 5: RASSAR's AR-based scanning interface and a detailed view of a detected issue. (1) During a scan, RASSAR shows detected problems in real-time via AR overlays, including (a) red spheres, which can be selected to view more information and to confirm/delete detection and (b) CV-based detections with green bounding boxes, a text label, and confidence score. To aid understanding of the CV field-of-view, we draw a (c) gray bounding box. We also show a mini-map (d) that adapts to users' orientation/position with real-time reconstruction results. (2) The user can click on identified issues (a) to view more information, see recommended solutions, and to (e) confirm/delete problems.

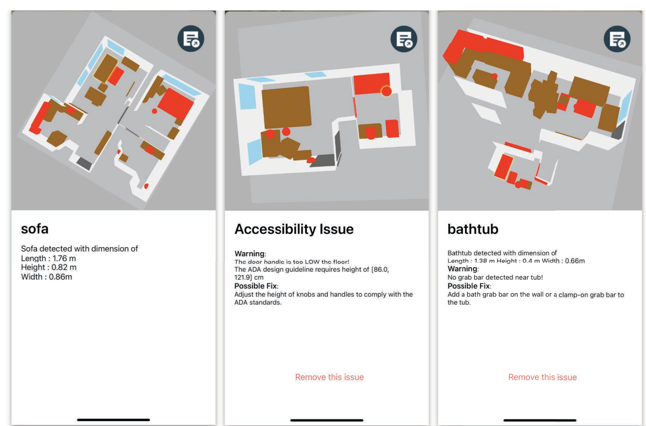

Figure 6: Three examples of the post-scan interactive summary of results. A user can interact with the 3D reconstruction, inspect detailed information about objects or issues, and remove any errant or disagreed upon issues. The top-right button lets user export scan results to a JSON file.

5.2.1 Detection performance. For detection performance, we calculate the number of true positives (*TP*), false positives (*FP*), and false negatives (*FN*) based on whether RASSAR successfully detected an issue listed in the RASSAR accessibility rubric, reported an issue that did not appear in the rubric, or failed to detect an issue. Notably, we did not calculate true negatives since it entail RASSAR not reporting on accessible and safe items, which is not meaningful for this evaluation.

Based on TP, FP, and FN counts, we calculate four evaluation metrics, including **precision** (calculated as $\frac{TP}{TP+FP}$), **recall** (calculated as $\frac{TP}{TP+FN}$) , **F1 score** [45], and **accuracy** (calculated as $\frac{TP}{TP+FP+FN}$). These metrics assess the quality of RASSAR's output, how many issues RASSAR missed, and RASSAR's ability to capture existing issues and avoid false alarms.

5.2.2 Scanning consistency. To examine RASSAR's consistency across scans (three per indoor space), we use Krippendorff's alpha [34], a common measure to assess agreement level among multiple raters. Specifically, we considered each scan a distinct rater and treated each space's accessibility and safety issue as a scoring task.

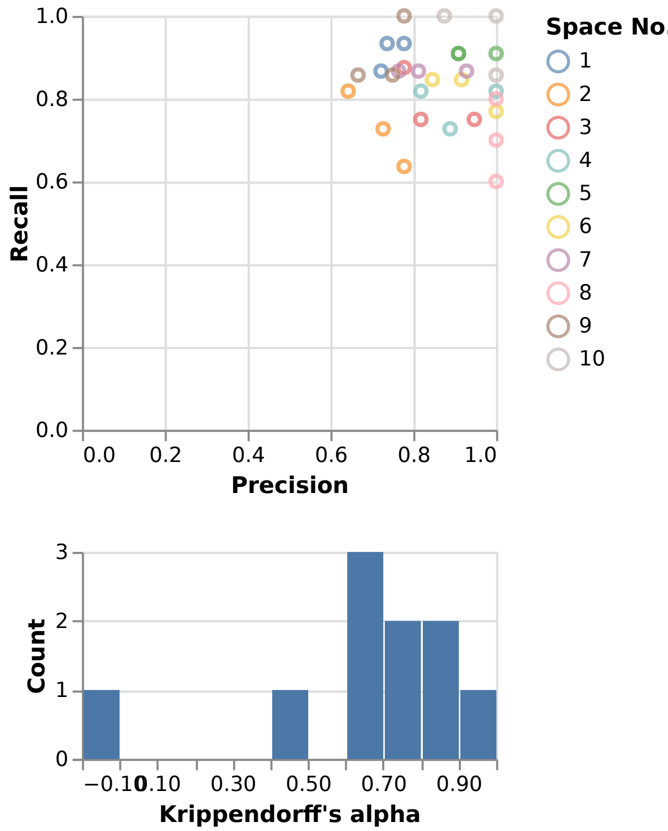

Figure 7: RASSAR's technical evaluation performance over ten indoor spaces. (Top) A scatter plot of precision and recall over 30 scans in 10 home spaces. (Bottom) A histogram of Krippendorff's alpha values across 10 home spaces (3 scans each).

5.2.3 Scanning time. Finally, we computed the average scanning time for each indoor space using screen recordings of scans.

5.3 Evaluation Results

Table 4 and Figure 7 shows RASSAR evaluation results. For readability, we present averaged performance stats for each space. The full results can be found in the appendix: Table 9. Overall, our analysis shows that RASSAR can effectively identify indoor accessibility and safety issues, with an average precision of 0.86, recall of 0.83, F1 score of 0.84, and accuracy of 0.72. We observe that most Krippendorff's alpha values fall in the range between 0.4 and 0.7, which indicates "substantial consistency" [27]). Finally, RASSAR scanning took 99.9 seconds on average (*SD*=27.4), much faster than manual auditing, which took the lead author approximately 10 mins/space.

5.4 Performance Analysis

Below, we describe more detailed findings related to performance as a function of issue and potential error causes.

5.4.1 Performance by accessibility & safety issue. Unsurprisingly, RASSAR's technical performance varies across accessibility and safety issue. In Table 5, we show individual performance metrics for 13 commonly encountered issues. Almost all exhibit strong detection performance, with F1 scores exceeding 0.65. Some issues, like '*bed height*' and '*cabinet height*', even achieved 1.0 accuracy. However, there is one notable exception: '*counter height*'. This particular issue, whose rubric requires a counter surface height of between 28 and 34 inches, shows subpar performance, a result that can be attributed to the RoomPlan API consistently classifying '*kitchen counters*' as '*storage units*.' This systematic error causes RASSAR to ignore '*counter height*' in most scans.

5.4.2 Causes of error. To better understand RASSAR errors, we classified them into six categories (Table 6). About half of all errors come from the object detection model, YoloV5, due to misclassifications (*i.e.,* the YOLO model reported incorrect category labels for detected objects). Because indoor spaces contain many similar objects, misclassification is a significant technical challenge. For example, condiment bottles were misclassified as medicine, drawer handles were perceived as grab bars, and bed sheets were classified as rugs, leading to invalid results. These errors usually cause false positives, which can be alleviated by manual checking and filtering, as discussed in Section 4.3.2.

The other primary cause of error was due to RoomPlan API limitations, particularly RoomPlan misclassifications. The RoomPlan API provided inaccurate object category labels, which led RASSAR to overlook underlying accessibility issues related to that object. For example, RoomPlan classifying a kitchen counter as storage, causing RASSAR to ignore underlying counter height issues.

6 STUDY 3: USER STUDY

Finally, for our last evaluation, we performed a user study with six participants across our stakeholder groups, including two wheelchair users, one older adult, two new parents, an OT, and a person with severely low vision (legally blind)—see Table 7. Among the wheelchair users, P1 used a manual chair and P4 an electric wheelchair—both had high-functioning upper-body motor control. Because we also envision RASSAR being used by non-stakeholders (*e.g.,* Airbnb hosts), we also recruited one additional participant. For recruitment, we used mailing lists, outreach to local disability groups, and snowball sampling.

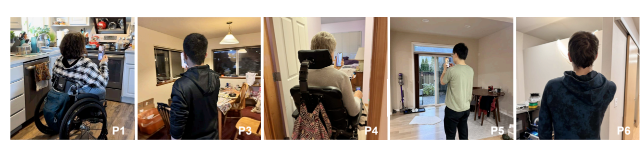

Figure 8: Study 3 participants conducting RASSAR scans.

6.1 Procedure

For the user study, two researchers visited participants' homes to conduct a three-part investigation: first, one researcher manually

Table 4: Information about the ten home spaces and RASSAR's performance results.Scanning time was measured in seconds. Precision, recall, accuracy, F1 score and Krippendorff's Alpha are described in Section 5.3. Performance metrics are averaged for each space. Raw scan performance data can be found in Appendix C

ID	Home type	Size (sqm)	Rooms Scanned	Average Precision	Average Recall	Average F1 Score	Average Accuracy	Krippendorf Alpha	Scan Time
S1	Apartment	65	3	0.75	0.91	0.82	0.70	0.73	113
S2	Apartment	63	2	0.72	0.73	0.72	0.56	0.7	120
S3	House	45	4	0.85	0.79	0.81	0.69	0.67	148
S4	Apartment	55	3	0.90	0.79	0.84	0.73	0.82	80
S5	Apartment	50	3	0.94	0.91	0.92	0.86	1	84
S6	Apartment	90	4	0.92	0.82	0.87	0.76	0.83	125
S7	Apartment	65	3	0.84	0.87	0.85	0.74	0.62	96
S8	Apartment	50	3	1.00	0.70	0.82	0.70	0.69	80
S9	House	24	2	0.73	0.90	0.81	0.68	-0.05	53
S10	House	60	3	0.92	0.88	0.90	0.82	0.43	100
			Average	**0.86**	**0.83**	**0.84**	**0.72**	**0.64**	**99.9**

Table 5: Detection performance of different accessibility/safety issues. GT stands for ground truth from manual auditing. Prec is the abbreviation of precision. F1 is short for F1 score. Acc is the abbreviation of accuracy.

Category	Issue Name	Count of GT	Count of TP	Count of FP	Count of FN	Precision	Recall	F1 Score	Accuracy
Object Dimension	Counter Height	42	3	1	39	0.75	0.07	0.13	0.07
	table height	42	38	8	4	0.83	0.91	0.86	0.76
	Door radius	27	17	3	10	0.85	0.63	0.72	0.57
	Bed Height	15	15	0	0	1.00	1.00	1.00	1.00
Object Position	Sink height	57	54	0	3	1.00	0.95	0.97	0.95
	Cabinet Height	48	48	0	0	1.00	1.00	1.00	1.00
	Grab bar height	15	12	8	3	0.60	0.80	0.69	0.52
Existence of Risky Item	Rug	48	48	2	0	0.96	1.00	0.98	0.96
	Medication	21	19	18	2	0.51	0.91	0.66	0.49
	Knife	15	14	7	1	0.67	0.93	0.78	0.64
	Scissors	15	15	0	0	1.00	1.00	1.00	1.00
Non-existence of Assistive Item	No Grab bar near toilet	27	24	0	3	1.00	0.89	0.94	0.89
	No Grab bar near tub	18	16	0	2	1.00	0.89	0.94	0.89

Table 6: The causes for RASSAR scan errors

Cause Name	Description	Total count	% across all errors
RoomPlan Misclassification	RoomPlan API misclassified an object	42	32.8
RoomPlan Measurement	RoomPlan API provided inaccurate object measurement	13	10.1
RoomPlan Miss	RoomPlan API missed an object	11	8.6
YOLO Misclassification	YOLO misclassified an object into another class, or falsely report an non-existing object	55	43.0
YOLO Miss	YOLO missed an object of interest	3	2.3
Raycast Issue	Raycasting process went wrong, resulting in missing or misplacement of object	4	3.1

conducted a ground truth inspection (similar to Study 2) in selected rooms (*e.g.,* kitchen, living room, and bathroom). Second, participants were provided with an iPhone 13 Pro Max with RASSAR installed. After a brief tutorial, they were asked to independently conduct a RASSAR scan of the same rooms. The research team observed the scanning behavior and took notes. Third and finally, the research team conducted a semi-structure debrief interview about RASSAR, inquiring about the overall experience, ideas for future work, and concluding with 7-point Likert scale ratings for usability, usefulness, perceived accuracy, and willingness to use RASSAR in the future (see Table 7). For analysis, we compared ground truth to RASSAR's detections (similar to Section 5.1) and thematically analyzed the interview data.

6.2 Findings

Overall, all six participants could independently use and scan their space with RASSAR, rating the app highly usable and accurate (*avg*=5.5 and 5.8 out of 7, respectively). Below, we expand on the technical performance, usability, usefulness, and user suggested improvements and application areas.

Technical Performance The scans resulted in an average precision and recall of 0.79 and 0.73, which is slightly lower than the scanning performance in Study 2, where precision was 0.86 and recall was 0.83. This difference can likely be attributed to Study 2's scans being performed by a single member of our research team, whereas in the current study, actual stakeholder users conducted the scans. When asked to rate their perception of RASSAR's detection performance, the average response from participants was also high: 5.8/7 (*min:* 5). "*The 3D reconstruction results are way better than my imagination*" (P5). Regarding scanning speed, participants completed their RASSAR-based scans in 3.3 minutes on average—3.5x faster than the ground truth manual auditing (*avg*=11.8min).

Usability. As noted above, all six participants successfully finished their home scans with RASSAR and rated the app highly usable (*avg=5.6/7; min: 5*). We observed different scanning practices, which may have also impacted technical performance. For example, P3, P4 and P6 constantly tilted phone up and down during scan, while P2 and P5 fixed phone vertical thus missed accessibility and safety issues on the floor. This oversight may be alleviated by visual or audio hints for missed indoor surfaces during scan. For P6, the low vision user, he was able to complete his scan with the audio assistance feature. Interestingly, though unexpected, other participants also found utility in the audio assistance. For example, both P4 and P5, who are sighted, conducted RASSAR scans with audio feedback enabled, which they felt increased their awareness of the scan progress and detected issues. "*The audio helped me a lot in understanding what's happening and what should I focus on during the scan.*" (P5)

Usefulness. In terms of perceived usefulness, the results were more nuanced: P3 and P4 rated usefulness as 6/7 because "*I would never know that the throw rug could be an issue*" (P3) and "*These results will be potentially useful if I want to pick a new home*" (P4). However, P1 and P2 rated usefulness as 4/7. P1, a manual chair user, felt that the ADA-based issues did not match her needs since "*My house is very usable to me, but in RASSAR's head, it wasn't*". Interestingly, P1 still rated the app highly usable and wanted to use the app in the future. For the OT (P2), they wanted RASSAR to be more customizable ("*it's not customized enough*")—a feature we hope to support in the future. P6, who is low vision, provided high ratings for all aspects except usefulness. He found the detected issues interesting and helpful, but rated usefulness low because the last part of the scan process—the scan summary of results—was not as accessible as he needed.

Potential applications. In the debrief interviews, participants offered a variety of use cases for RASSAR. P1, who rated full marks for her willingness to use RASSAR, envisions RASSAR as a way to scan, assess, and share the accessibility of public spaces: "*It would be really helpful in public spaces. I'm on several Facebook groups for people with disability. And we will all turn to write reviews of different places that we go. [With RASSAR], we can have a more objective way to share that information.*" Similarly, P2 (the OT), felt that RASSAR could be used to help raise awareness about accessibility issues and scale better than on-site OT inspections: "*What OT can do [to help people] is very limited. There are so many people in need but very few have access to OT service.*". Although P2 rated low for her own willingness to use, she was happy to recommend RASSAR to others. "*I might not use it since I already have this knowledge. But I would recommend it to my family or anyone in need. It's so convenient and way better than me lecturing them!*"

P3 found more personal use cases instead. "*If I move to a new home, or when I get injured someday, I might want to use this (to check for home safety)*". Similarly, P4 thinks RASSAR can be used in auditing new homes to help make the most suitable purchase. "*It would be helpful for auditing another place.*" P5 thinks RASSAR could be helpful for child-proofing if more children-related issues get implemented in the future.

System Improvements. Participants provided valuable feedback on enhancing user interaction with the system. A prevalent set of suggestions regarded the summary view (Figure 6), particularly in improving the manipulation of the 3D model (P1) and organizing scan results by specific rooms, such as the kitchen, bedroom, and restroom (P2). Additionally, both P2 and P5 wanted the scan summary in a list format. P6 also echoed this suggestion since a list view is more compatible with screen readers. Another set of recommendations revolved around improving scanning support. P5 suggested additional audio or visual cues to alert users when they miss certain indoor surfaces, like the floor. Similarly, P6 wanted extra audio alerts for the proximity of indoor objects, in order to prevent BLV users from bumping into barriers. Furthermore, P3 advocated for more direct visual guidance, such as arrows, to assist users in conducting thorough scans without overlooking key areas.

7 DISCUSSION

We introduce the first mobile AR system to detect accessibility and safety issues in home spaces. Using RASSAR, individuals can semi-automatically audit their home spaces and generate real-time 3D reconstructions that highlight accessibility and safety issues. Additionally, we conducted three studies to examine real-world needs, technical performance, and user experience of our proposed method. Below we elaborate on the implications of our findings and opportunities for future work.

Table 7: User study demographics, scan stats and user ratings.

ID	Stakeholder Identity	Home Type	Scan Area (sqm)	Rooms Scanned	Manual Audit Time (Min)	Scan Time (Min)	Prec.	Rec.	Acc	Ratings from 1-7			
										App usability	Usefulness of results	Detection performance	Willingness to use
P1	Wheelchair user	House	120	4	12	5.02	0.74	0.67	0.54	6	4	6	7
P2	OT	Apartment	43	2	21	3.08	0.54	0.88	0.5	5	4	5	1
P3	None	House	60	2	14	2.25	0.92	0.85	0.79	5	6	6	4
P4	Wheelchair user, older adult	Apartment	70	4	10	3.25	1	0.73	0.73	6	6	7	6
P5	New parents	House	150	3	7	3.38	0.67	0.46	0.38	6	-	5	5
P6	BLV	Apartment	55	3	7	3.05	0.88	0.78	0.7	5	1	6	6
				Average	11.83	3.34	0.79	0.73	0.61	5.5	4.2	5.83	4.83

7.1 Application Scenarios

Unlike prior work in automatic accessibility auditing—which often involves complex data collection processes [8, 17] or specific hardware [7, 51]—the RASSAR system is a plug-and-play application on smartphones. This ease of use significantly expands its appeal and potential applications. From the formative study (Section 3.2.3) and user study (Section 6), we identified numerous possible use-cases for RASSAR, which we expand on below.

Prior-visit Auditing. One common challenge identified in the formative study is the uncertainty about a location's accessibility before visiting, including rental spaces, such as hotel rooms or Airbnb accommodations, public spaces, like restaurants and shops, as well as friends' or family's homes. Based on our user study feedback (Section 6), RASSAR emerges as a practical solution by offering a standardized scanning and detection process for previewing accessibility and safety issues. Site owners could employ RASSAR to ensure that their spaces meet general accessibility requirements or share the scan results to help people preview and evaluate a space before visiting. Future work should examine sharing interfaces to support this desired feature.

Improve Spaces to Accommodate Life Changes. All lives undergo transformation, which can impact accessibility and safety. For people undergoing significant life events such as illness, childbirth, or the need to care for older family members, we found that RASSAR can serve as a convenient evaluation tool that raises awareness of potential risks under such changes, and could also provide home renovation suggestions such as removal of dangerous items and adjustment of object dimensions.

Complement OT's Home Visits. As previous research [46] and our own studies with OTs indicate, it is often challenging for individuals to request, schedule, and pay for OT home visits. With RASSAR, OTs can offer remote assistance by reviewing the system's scanning results, which not only encompass visual information but also include 3D positions and measurements. Consequently, remote auditing processes could become more standardized, efficient, and precise compared to existing methods like video calls.

Beyond residential. While RASSAR is presently designed for residential spaces, its technical framework could be applied to non-residential areas such as offices, schools, and restaurants. In initial work, we conducted successful tests of RASSAR in two offices. In the future, we would like to incorporate new rubrics for non-residential spaces and examine methods to upload and view assessments.

7.2 Detection Performance

As described in subsection 5.3 and section 6, RASSAR yielded an average precision/recall of 0.86/0.83 when operated by our research team, and 0.79/0.73 by stakeholder participants. Compared with manual auditing, scans are also about 3.5x faster. While preliminary, these results are promising. Still, RASSAR's performance could be improved. Most error cases were caused by deficiencies in our YOLOV5 model (Section 4.1.2) and the RoomPlan API. In the future, we plan to further improve RASSAR performance by expanding our object detection model to also detect furniture categories to correct RoomPlan misclassifications, and also expand training dataset on micro indoor objects to improve detection performance. More work is necessary to determine what accuracy is required for the different application scenarios proposed above.

7.3 Accessibility Issue Scope

Currently, RASSAR detects 20 types of accessibility and safety issues across four categories (Figure 4). We plan to expand this list based on needs found in the literature (*e.g.* detecting sharp edges of furniture [42]), our formative study findings (*e.g.,* home entrances, stairs and bath facilities), and user study findings (*e.g.* wheelchair maneuvering spaces).

7.4 Potential Beyond the ADA

The current RASSAR system relies on ADA design guideline as the main source of accessibility rubrics. But as found in both our formative and summative user studies, ADA design guidelines are often minimum requirements and may not fit everyone's needs. "*ADA is just a fixed standard for reference, thus it cannot ensure fitting on everyone.*" (P2, Study 3) Similarly, one wheelchair participant from Study 3 complained that she once found out a non-ADA hotel room also worked great for her when the ADA units were booked out. In this case, the binary classification of "ADA accessible" became exclusionary. With RASSAR's custom JSON-based rubric definitions, assessments could be personalized to individual needs. Future work should explore rubric authoring interfaces.

8 CONCLUSION

We introduced RASSAR, a mobile AR system that semi-automatically audits indoor residential spaces for accessibility and safety issues.

Built with state-of-the-art mobile LiDAR scanners and mobile computer vision models, RASSAR efficiently and effectively identifies, localizes, and visually displays accessibility and safety issues and provides recommendations for mitigation. RASSAR is both customizable, letting users specify their target accessibility communities, and verifiable, letting users manually verify detected issues. Our technical evaluation (Study 2) in ten home spaces shows that *RASSAR*'s performance is accurate, consistent, and efficient. Our initial user study (Study 3) further demonstrates RASSAR's potential among stakeholder groups. Our work advances the literature on indoor accessibility and safety auditing, contributes indoor accessibility object detection model and dataset to the research community, while simultaneously opening up new research avenues for human-AI collaborative indoor auditing.

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A JSON EXAMPLE

```
"Counter":{
    "Dim_Height":{
        "Community":["Wheelchair"],
        "Dependency":null,
        "Dimension":{
            "Comparison":"Between",
            "Value":[28,34]
        },
        "RelativePosition":{
            "Comparison":null,
            "Value":null
        },
    "Existence":null,
    "Note":"replace PLACEHOLDER to either 'short' or 'tall' depends on the actual height of the counter.",
    "Message":"Warning: Counter is too PLACEHOLDER.",
    "Description":"According to ADA compliance, counters must be at the proper height (this often is 28-34 inches from the floor).",
    "Suggestions":["Replace to an adjustable height counter"],
    "Sources":[
    {"name":"2010 ADA Standards for Accessible Design", "url":"https://www.ada.gov/regs2010/2010ADAStandards/2010ADAstandards.htm"},
    {"name":"Aging in place: Designing, adapting, and enhancing the home environment","url":"https://scholar.google.com/scholar?hl=en&as_sdt=0%2C48&q=Aging+in+Place+Designing%2C+Adapting%2C+and+Enhancing+the+Home+Environment&btnG="}]
    }
},

"Cabinet": {
    "Pos_Height": {
      "Community": ["Wheelchair"],
      "Dependency": null,
      "Dimension": {
        "Comparison": "LessThan",
        "Value": [27]
      },
      "RelativePosition":{
            "Comparison":null,
            "Value":null
        },
  "Existence": null,
  "Note": null,
  "Message": "Warning: The cabinet is too TALL!",
  "Description": "According to ADA compliance, the height of cabinets should be no more than 27 inches from the floor.",
  "Suggestions": [ "Move things you frequently use to places within easy reach."],
  "Sources": [
    {"name":"2010 ADA Standards for Accessible Design", "url":"https://www.ada.gov/regs2010/2010ADAStandards/2010ADAstandards.htm"},
    {"name":"HSSAT","url":"https://www.tompkinscountyny.gov/files2/cofa/documents/hssat_v3.pdf"}]
    }
  },

"GrabBar_Existence_Tub": {
"ExistenceOrNot": {
  "Community": ["Wheelchair", "Elder"],
  "Dependency": ["Tub"],
  "Dimension": {
    "Comparison": null,
    "Value": null
  },
  "RelativePosition":{
            "Comparison":"LessThan",
            "Value":[27]
        },
  "Existence": true,
  "Note": null,
  "Message": "Warning: No grab bar detected near tub!",
  "Description": "For safety, there should be grab bars near tub.",
  "Suggestions": ["Add a bath grab bar on the wall or a clamp-on grab bar to the tub."],
  "Sources": [
    {"name":"HSSAT","url":"https://www.tompkinscountyny.gov/files2/cofa/documents/hssat_v3.pdf"}]
}
},
"Knives": {
"ExistenceOrNot": {
  "Community": ["Children"],
  "Dependency": null,
  "Dimension": {
    "Comparison": null,
    "Value": null
  },
  "RelativePosition":{
            "Comparison":null,
            "Value":null
        },
  "Existence": false,
  "Note": null,
  "Message": "Warning: Knives have been detected in a dangerous place!",
  "Description": "For safety, no knives should be present on reachable surface.",
  "Suggestions": ["Move out of reach of children"],
  "Sources": []
}
```

B ALL SUPPORTED ACCESSIBILITY AND SAFETY ISSUES

Table 8: 20-item RASSAR Accessibility and Safety Issues.

Issue name	Category	Rubirc (inch)	Rubric (cm)
Bed height	Object Dimension	20 - 23	50.8 - 58.42
Table height	Object Dimension	28 - 34	71.1 - 86.4
Counter height	Object Dimension	28 - 34	71.1 - 86.4
Door Radius	Object Dimension	>32	>81.3
Opening Width	Object Dimension	>32	>81.3
Cabinet height	Object Position	<27	<68.6
Sink Height	Object Position	<17	<43.1
Door Handle Height	Object Position	34 - 48	86.4 - 122
Knob Height	Object Position	34 - 48	86.4 - 122
Light switch	Object Position	15 - 48	38.1 - 122
Electric socket	Object Position	15 - 48	38.1 - 122
Grab bar height for adults	Object Position	33 - 36	83.8 - 91.4
Grab bar height for children	Object Position	18 - 27	45.7 - 68.6
Fire alarm	Lack of Assistive Item	Should exist	
Grab bar near tub	Lack of Assistive Item	Should exist	
Grab bar near toilet	Lack of Assistive Item	Should exist	
Rug	Risky Item	Shouldn't exist	
Scissors	Risky Item	Shouldn't exist	
Knife	Risky Item	Shouldn't exist	
Medication	Risky Item	Shouldn't exist	

C TECHNICAL EVALUATION FULL RESULTS

Table 9: Information of ten scanned home spaces and RASSAR evaluation results on them. GT refers to ground truth obtained from the RASSAR accessibility rubrics. Scanning time was measured in seconds. Definition of precision, recall, accuracy, F1 score and Krippendorff's Alpha are introduced in subsection 5.3

Space	Size (sqm)	Home Type	Rooms Scanned	Count of GT	Prec.	Recall	F1 Score	Accuracy	Krippendorf Alpha	Scan Time
					0.74	0.93	0.82	0.70		
S1	65	Apt	3	15	0.72	0.87	0.79	0.65	0.73	113
					0.78	0.93	0.85	0.74		
					0.64	0.82	0.72	0.56		
S2	63	Apt	2	11	0.73	0.73	0.73	0.57	0.7	120
					0.78	0.64	0.70	0.54		
					0.78	0.88	0.82	0.70		
S3	45	House	4	24	0.82	0.75	0.78	0.64	0.67	148
					0.95	0.75	0.84	0.72		
					0.89	0.73	0.80	0.67		
S4	55	Apt	3	11	1.00	0.82	0.90	0.82	0.82	80
					0.82	0.82	0.82	0.69		
					0.91	0.91	0.91	0.83		
S5	50	Apt	3	11	0.91	0.91	0.91	0.83	1	84
					1.00	0.91	0.95	0.91		
					0.92	0.85	0.88	0.79		
S6	90	Apt	4	13	0.85	0.85	0.85	0.73	0.83	125
					1.00	0.77	0.87	0.77		
					0.76	0.87	0.81	0.68		
S7	65	Apt	3	15	0.81	0.87	0.84	0.72	0.62	96
					0.93	0.87	0.90	0.81		
					1.00	0.70	0.82	0.70		
S8	50	Apt	3	10	1.00	0.60	0.75	0.60	0.69	80
					1.00	0.80	0.89	0.80		
					0.78	1.00	0.88	0.78		
S9	24	House	2	7	0.75	0.86	0.80	0.67	-0.05	53
					0.67	0.86	0.75	0.60		
					0.92	0.86	0.89	0.80		
S10	60	House	3	14	0.92	0.86	0.89	0.80	0.43	100
					0.93	0.93	0.93	0.87		
				Average	**0.86**	**0.83**	**0.84**	**0.72**	**0.64**	**99.9**