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Understanding Perceived Utility and Comfort of In-Home General-Purpose Sensing through Progressive Exposure

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A fundamental paradigm shift for in-home sensing is apparent. *Special-purpose sensing*, where there is a one-to-one relationship between sensors and applications, is evolving into *general-purpose sensing*, where there is a many-to-many relationship between sensors and applications. This new shift may impact how individuals think about in-home sensing, where utility and comfort are often linked to *applications* rather than *sensed data*. We explore the evolution of individuals' perceptions as they become increasingly and contextually aware of sensor capabilities and data characteristics. Through a multi-phase study where 12 participants were progressively led through six exposure conditions across laboratory and home environments, we find that exposure changes represent inflection points for perceptions of utility and comfort with data collection. These changes define opportunities for increasing trust in sensing infrastructures via data- and context-aware interventions, managing over-reliance on awareness notifications, and providing data-enabled "what if" analyses to balance comfort and utility within an individual's unique context and environment.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: Privacy, Home, Ambient Devices, Internet of Things, Field Study

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1 INTRODUCTION

Smart-home device adoption is increasing, with an annual compound growth of 22.3% expected through 2026[1]. The majority of current smart-home technologies incorporate built-in sensors

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[1]https://www.globenewswire.com/news-release/2022/08/18/2501085/0/en/The-Smart-Homes-Market-Is-Expected-To-Reach-205-Billion-By-2026-Driven-By-The-Growing-Adoption-Of-Smart-Devices-As-Per-The-Business-Research-Company-s-Smart-Homes-Global-Market-Rep.html

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that drive novel interaction (e.g., microphones in a smart-speaker to support voice interaction) or understand activities occurring in physical spaces (e.g., motion detectors to control lights). As a result, the relationship between sensors and applications in the current generation of technologies is predominately *special-purpose*: the sensing needed to power an application is contained within the device associated with that application. This one-to-one approach has fundamental limitations; it does not scale or bring the full power of a home rich with sensors to bear across *multiple* applications. By contrast, so-called *general-purpose sensing* combines many sensors (usually into a single device) to be used for a multitude of applications and can increase overall sensing utility and unlock new applications and use cases [52]. Given the leap in capability, these approaches will likely dominate the next generation of smart-home technologies, potentially resulting in fundamental shifts in user expectations and perceptions of in-home sensing.

Understanding end-users perceptions, acceptance, and use of in-home sensing is an established, active area of research within the HCI and sensing communities. Particularly within CSCW, smart-home privacy has been a topic of high importance [53, 105] as smart-homes can support coordination and collaboration between inhabitants [57, 72] either through direct (e.g., signaling and communication [45]) or remote (e.g., presence detection [23]) interactions. Understanding user perceptions of home sensing becomes even more important as people increasingly shift to working remotely from home [75]. Much of the past work concentrates on developing novel techniques or design guidelines for more privacy-sensitive in-home sensing such as microphones [8, 39], home robots [16, 30, 32, 81], cameras [33, 41, 58, 76, 85, 93, 107, 108], and arrays of multiple sensors [37, 43, 52, 59, 63]. Significant research has also focused on end-user acceptance and comfort with data collection. These works have primarily contributed design principles based on a detailed study and synthesis of end-user perceptions of comfort and utility across myriad applications and environments. However, these insights are largely derived from applications within special-purpose sensing paradigm like home healthcare [2, 11, 13, 47], in-home occupancy and activity detection [50, 51, 65, 67, 92], and smart cameras [4, 6, 32, 38, 67]. The emergence of the general-purpose sensing paradigm necessitates re-examining findings of user comfort with sensing through the lens of the *data captured* rather than specific applications enabled, as well as how users' understanding of this data evolves *over time and context*. Thus, the research question we explore in this work is *how incremental exposure to sensor data values affects end-user perceptions of utility and comfort with data collection in a space.*

To investigate how sensor data values can impact end-user perceptions of comfort and utility, we engaged with twelve participants in a multi-phase study over the course of a year. In each phase, we introduced participants to a new ***exposure***, which we define as an event where participants experienced additional, incremental information about the sensors, building upon their prior knowledge. Through an extensive literature review, we identified that prior work was often framed around a subset of six progressive classes of exposure that included participants' baseline understanding of sensors, controlled laboratory activities, and in-home deployments of varied duration. Unlike prior work, our study progressively led participants through all six classes of exposure, providing insights into how perceptions of utility and comfort *evolve* in concert with increased exposure to distinct classes of in-home sensors and the data they collect. In the latter exposures, where we demonstrated the sensors in action, we also showed participants visualizations of the accompanying sensed data. To examine changes in participant sentiments, we presented the same questionnaire and conducted an interview after each exposure. Consequently, we could examine how each exposure impacted participant perceptions of sensed data along two dimensions: sensor type and exposure level. In contrast to previous research that examined user acceptance and perceived utility of sensors in specific environments and use cases, we focused on visualizing sensed data values to participants while trying to avoid associating each sensor with only a singular use case.

The contributions of this work are:

(1) In this work, we present new insights that weave together the broader field of existing research, which has largely been siloed in subsets of specific exposures or technologies, often within the context of a particular use case or application (e.g., eldercare and home monitoring). Our work highlights how end-user acceptance and perceptions of utility and comfort with data collection are situated across exposures and technologies and, more importantly, **the dynamic nature of these perceptions across these boundaries**.
(2) Through our findings, we postulate that different **exposure points provide valuable opportunities to reinforce data collection awareness**, which is necessary to build trust in and acceptance of in-home general-purpose sensing. Further, we found that users are able to effectively associate new or differing patterns in the sensed data with novel activities in the space (e.g., patterns from a visitor or pet). These moments could prime users to think critically about how these new data patterns can be used in their own context within a general-purpose sensing framework.

2 BACKGROUND AND RELATED WORK

The use of sensing technologies in the home is a long-studied topic in the HCI and hardware sensing communities. Our work is directly motivated by the continued advancement of these techniques and applications, particularly breakthroughs that demonstrate the potential for general-purpose sensing approaches [29, 52]. Our work is focused on this potential and centers on understanding end-user perceptions of these technologies in their home as their familiarity evolves. Furthermore, we identify strategies to drive end-user comprehension of, and agency over, the data being captured in their home.

Within this focus, our work is situated between three distinct categories of prior work: (1) the development of designs, systems, and studied prototypes that intentionally address privacy and acceptance concerns related to sensing in the home; (2) studies that examine how privacy concerns and acceptance differ based on the specific sensing technology employed; and (3) studies that examine how privacy concerns and acceptance change over time as users increase their exposure to data collection and application use.

2.1 Privacy preserving technologies and guidelines

Many novel sensing techniques have been developed and validated to preserve privacy by explicitly avoiding privacy-sensitive data collection. At the heart of these works is the development of techniques to gain acceptance and awareness of what data is being sensed and for what purpose. Several prototype systems have demonstrated that the use of lower-fidelity sensing can still achieve desired sensing objectives [1, 8, 30, 43, 71, 107]; for instance, [43] demonstrates the use of a time-of-flight sensor to track people with the same accuracy as RGB camera-based techniques. Other approaches seek to limit the association of privacy-sensitive data with user identity; particularly effective use of this approach was demonstrated by [9], which increased entropy in general-purpose sensing traces to preserve user identity. Reactive sensing techniques have also been developed, making sensors aware of the context in which they exist, from location [9, 37, 60, 93] to activity [37, 59, 63, 64, 102]. For instance, [102] developed an on-device technique to prevent data collection when unclothed humans are in proximity. Finally, another approach is artificially narrowing sensing ability [16, 33, 39, 41, 52, 58, 76, 81, 85, 108]. For instance, [39] demonstrates that the exclusion of audio data at frequencies used for human speech can still allow the audio to inform activity recognition techniques.

	78	4 67	32 22	28 62	55	106	7 66 6 104	54 49	2	42	110 12	92 109	5	82	16	48	77	18	38 95	56	101	46	70	69 11	90	100	51	40	50	47	103	19	94	68	Our Work
Accel.																																			
Light																																			
Mic.																																			
PIR																																			
Radar/Lidar																																			
Temperature																																			
Camera																																			

Table 1. Some representative exposure and sensor technology works organized by exposure levels and sensing modalities. The column headers cite the specific works, while the rows represent different sensors. The colors represent the different exposures: red: *BL-1*, blue: *VD-2*, purple: *CD-3*, green: *LD-4*, orange: *1W-5*, and yellow: *1M-6*. Cells with several colors indicate works that had multiple exposures corresponding to the colors listed before. For example, [70] explored microphone and camera sensors in exposures *BL-1*, *VD-2*, and *1M-6*.

These successful explorations of privacy-aware sensing have also led to the development of guidelines for their development and use [36, 44, 61, 73, 83, 84, 86, 87, 89, 97]. There is significant breadth in what these guidelines address. As an example, [61] provides techniques and structures to mediate engineering needs (i.e., best-fidelity sensed data) and regulatory needs (i.e., privacy-enhanced sensed data). Others help identify privacy risks [36, 44, 83, 84, 97]; for instance, [83] provides design recommendations that address unique privacy concerns of children, elderly and disabled persons.

2.2 Prior studies of in-home sensing acceptance and perceived utility

Extensive prior research has examined user acceptance and the perceived utility of in-home sensing. A detailed review of the HCI and sensing literature identified and categorized 46 relevant prior studies of in-home sensing. In addition, we found that these studies were often framed around six classes of exposures to sensors and the data that they capture: (*BL-1*) where participants were surveyed or interviewed about their baseline understanding of technologies, (*VD-2*) where a verbal explanation or related media (visualizations or videos) was presented to the participants, (*CD-3*) where participants were shown actual examples of the technology in use, (*LD-4*) where the participants interacted with the technology and were presented with the associated data, (*1W-5*) where the technology was deployed to the participant's home for approximately one week, and (*1M-6*) where the technology was deployed at the participant's home for one month or longer. We note that the surveys and interviews conducted in *BL-1* served to gather a baseline of each participant's understanding and comfort with the sensors. Other than a short description of the sensor (see Appendix A.1), they were not used to inform or expose any additional information about the sensors to participants. Seven common sensing technologies were observed: accelerometer, light, microphone, passive infrared (PIR), radar/lidar, temperature, and RGB camera. Thus, we categorized this prior work along two dimensions: technologies investigated and levels of exposure studied. We summarize this organization in Table 1.

2.2.1 Different technologies, single exposure. Many prior studies that have examined sensing comfort and utility were performed within a single context of use or setting, which we refer to as an exposure (see Section 1). These studies used questionnaires and interviews in which a sensing technology was presented to the participant with no description or explanation of the sensor or its sensing ability (red citation blocks in Table 1), or the participant was only presented with a description of the sensor or its sensing ability without any demonstration or observation of the sensor's data output (blue citation blocks in Table 1).

In the former (i.e., red citations), the common objective, broadly, was to understand variations in privacy expectations and preferences for technologies assumed to be understood by participants [4, 32, 67]. The studies often focused on specific use cases for each technology, such as camera usage for security [4]. In the latter (i.e., blue citations), descriptions of technologies were provided in written, verbal, or media (visualizations or videos) form [6, 7, 92, 109], or descriptions were elicited as part of group discussions [2, 66, 104]. These studies also focused on specific use cases or usage environments.

2.2.2 Different technologies, multiple exposures. As visually explained in the right side of Table 1 (specifically, [16, 38, 50, 51, 56, 68–70, 82, 94, 95, 101]), exposures varied from lab demonstrations to in-home deployments that included explanations of collected data. Exposures also varied in deployment length, ranging from two days to upwards of several years. It is important to note that while these studies covered multiple exposures, many only collected user sentiment data after all exposures were experienced by users (i.e., at the end of the study). This limits the ability of these studies to infer how sentiment and understanding of the technologies changed through different exposures.

Several studies asked users to interpret, explain, or demonstrate an understanding of the collected data. These studies often tied the sensor data to a particular use case, for instance, monitoring indoor temperature [19, 51, 94]. Similarly, [50] asked users to annotate sensor data collected from a short home deployment. Afterward, they asked participants to discuss and reflect on the sensors and data amongst each other. One of the main limitations they mention is the misuse and misunderstanding of data, demonstrating the importance of measuring end-user perceptions across different exposures. Many studies of in-home deployments focused on cameras and microphones, two of the most privacy-invasive sensors, and were often limited to assistive care use settings [11, 68–70]. While such studies inform how well end-users can understand sensing technologies in a specific scenario, the highly defined setting and motivation limit a broader understanding of general-purpose sensing. In contrast, our study was designed to avoid associating the sensing hardware and resulting data with a particular application or use setting. Our study examines end-user comfort and utility with *sensed data* throughout quotidian activities.

2.3 Situating this study within broader research context

Our study situates within these existing technologies and guidelines in two crucial ways. First, most prior work on privacy-aware sensors focuses on a one-to-one relationship between sensing and use in specific applications. We have argued that this paradigm is not sustainable as viable, many-to-many approaches emerge. Individual sensing innovations will need re-examination as a result of this paradigm shift. Second, most prior guidelines assume or explicitly define the connection between sensed data and that data's use in specific applications. A many-to-many sensing model will weaken these assumptions. Our study provides insights into perceptions of utility and comfort from a data-centric, general-purpose sensing perspective, explored across several use contexts and sensing technologies. Results and implications from our study can guide the development of next-generation sensors and design guidelines for many-to-many, general-purpose sensing paradigms.

Despite prior work covering many different technologies across many different exposures, Table 1 shows that these studies have primarily been isolated to *specific exposures* or *subsets of technologies*, often within the context of a particular use-case or application (e.g., eldercare and home-monitoring). This table identifies that despite extensive study, the research community still lacks a broader understanding of how end-user acceptance and perceptions of utility are situated across technologies and exposures and, *more importantly*, of the dynamics and relationships that

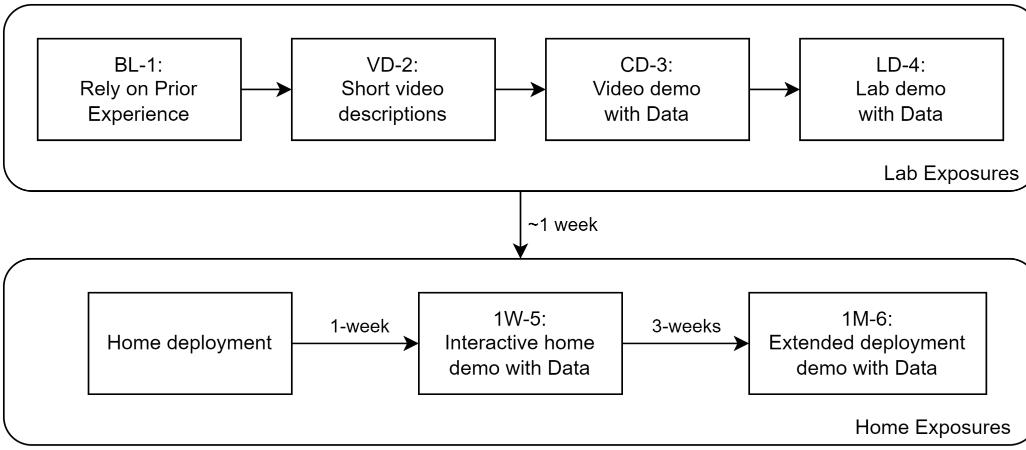


Fig. 1. Different exposure levels in the study. The top part of the figure shows the progression between lab exposures, and the bottom shows the progression between the home exposures.

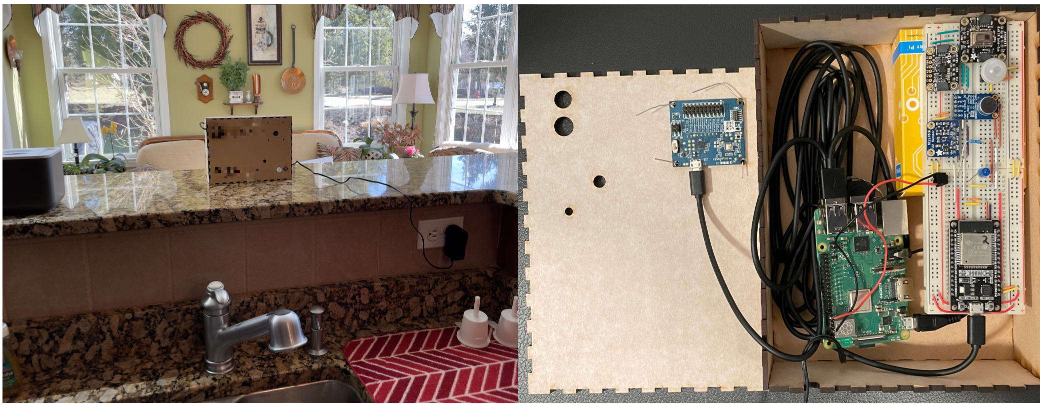
exist across these boundaries. Our work, also represented in Table 1, seeks to fill this gap. For instance, we observed that participants reported greater comfort with sensing in their home environment even though the sensor modalities remained the same (Section 4.3.3). On the other hand, we noted multiple cases of participants' perceived utility of the sensors going down as they had difficulty linking data to specific applications (Section 4.3.2).

3 METHODS

In this section, we describe our study setup and methodology in detail. Due to hardware limitations and fluctuating institutional and local COVID-19 policies, we staggered our study and deployments from November 2021 to June 2022.

3.1 Study Design

The study consisted of six different exposures synthesized from the broad categorization of studies performed in related work. In order of progression, these were a baseline pre-survey (*BL-1*), a static video description or explanation (*VD-2*), a contrived video demonstration of a series of actions and the associated sensor data (*CD-3*), an interactive laboratory demonstration involving quotidian activities and the resulting sensor data (*LD-4*), an interactive demonstration including sensed data following a one week home deployment period (*1W-5*), and an interactive demonstration including the resulting data following a one month home deployment period (*1M-6*). Lab exposures comprised the first four exposures, and home exposures formed the remaining two. Figure 1 shows the progression between these exposures. The lab visits were conducted at our institution, during which a single participant would experience exposures *BL-1* to *LD-4* within approximately three hours. Two to three researchers administered each session to a single participant. Lab sessions were audio-video recorded with the participant's consent. P15 did not consent to the video recording of the lab session. After the lab session, two to three researchers visited participant homes thrice over one month for home exposures (*1W-5* and *1M-6*). The first home visit to deploy the sensor box (Figure 2) was typically scheduled within a week of completing the lab exposures, depending upon participant and researcher availability (median: 4.5 days). It involved setting up the sensor box at the participant's home, which took about one hour. The next home visit for exposure 1W-5 would



(a) Closed sensor box deployed at P01's home. (b) Inside view of a sensor box.

Fig. 2. Sensors and the sensor enclosure used in the study. Specific sensors used are in Figure 3.

take place one week later, the final home visit for exposure 1M-6 would take place three weeks after that (one month from sensor deployment), and each home visit took 1.5 hours each and was audio-recorded.

Following each exposure, each participant completed a questionnaire from Naeini et al. [67]. The questionnaire presented six scenarios to the participants, one for each sensor included in the study. Each scenario included ten questions: nine Likert-scale and one open-ended question. The questions measured participants' perceived utility, comfort with data collection, and preferred notification frequency for each scenario. The questionnaire has been included in this article's appendix (Appendix A.1). We used the questionnaire to guide the interview process and identify where participant perceptions related to a sensor modality might have shifted after each exposure point. Thus, following each questionnaire round, we conducted a brief semi-structured interview with the participants to discuss their responses. For *BL-1*, which relied on the participants' prior knowledge about the presented sensors, we asked about their general thoughts and briefly discussed their ratings for each sensor. For the rest of the exposures, participants were asked at the start about their general thoughts regarding what stood out to them after that exposure. If a participant's rating changed from the previous exposure, the participant was also asked to explain or motivate any observed changes. Participants did not interact with the sensor during deployment, as we provided no computing resources to access live data visualizations. Further, we did not assume any literacy and wanted to ensure that the participants understood how to engage with the data and ask questions about it. Our objective was to have periodic assessments at set times and specific conversations with participants at those times. We note this is a typical methodology in this domain of study; it has been used extensively in the cited related work: 41 out of 45 of the surveyed papers conducted interviews, and 10 out of 13 surveyed papers included a sensor deployment in participant homes.

We did not use diary studies or ESMs since we could not control how long the user had access to the sensor data. ESMs and diary-based studies do not allow for deeper points of inquiry and suffer from response drop-outs [98]. Prior works that incorporated diary studies [40, 50, 54, 96, 103] or ESMs [98, 99] did so to collect ad hoc experiential feedback. However, this type of uncontrolled data collection could lead to different presentation amounts. Indeed, participants often differed in the number of activities logged during *1W-5* and *1M-6*. Moreover, we employed interviews after specific periods to ensure that participants saw and interacted with the data in a more controlled setting. The interviews further allowed them to ask questions and allowed us to make sure they understood the data.

We followed a data-first approach in this work rather than an application-first approach often used in prior literature [26]. Here, data-first refers to understanding participant perceptions around general-purpose sensing through interaction with data rather than specific applications (application-first), which is common in special-purpose sensing. While the scenarios we included in the questionnaire did list out an example application for each sensor, these were to contextualize the sensor use rather than tie the sensor to a specific application. Similarly, the marketing and educational videos shown to participants during *VD-2* listed multiple use-cases for a sensor rather than a single use-case to contextualize sensor usage scenarios.

3.1.1 Baseline pre-survey (BL-1). Similar to other survey-based studies that seek to understand individual perspectives related to sensing utility and comfort [4, 62, 79], with our first exposure, we aimed to understand participant perceptions of various sensing modalities based on their prior knowledge and experience. This would act as a baseline as participants are progressed to further exposures.

In this exposure, we gave the participants a terse description of the study; they were told that the study seeks to understand perceptions and preferences of in-home sensing technologies, followed by which they were given the study questionnaire (described above). The scenarios in the questionnaire provided a one-line description of the sensor and one example use case. For instance, *the living room has a light sensor that captures the light intensity that is used for detecting certain events (e.g., the TV is turned on).* Additional details about sensors and their functionality were not provided; participants could only leverage knowledge and experiences they had prior to beginning the study. A semi-structured interview followed the questionnaire.

3.1.2 Static video description or explanation (VD-2). Another common approach studies use in prior work is to explain the device or sensing purpose and describe or demonstrate potential applications. This can be through verbal explanations or media such as pictures and videos. This approach is used to improve participant familiarity or understanding to allow for more profound thought about utility and concerns about the use cases of these devices and data collection [7, 92, 104].

We presented our participants with a description of each sensor via a short video (one video per sensor). We either sourced videos from commonly available marketing materials of popular products (e.g., Amazon Echo Dot, SimpliSafe Motion Sensor[2]) that utilize a specific sensor or educational videos explaining how a sensor could be used in an application. For example, the video used to provide information about the accelerometer was an advertisement video for Micro:bit accelerometers, highlighting use cases for the device, such as fall detection, step trackers, and use in games. All videos were short, averaging around 45 seconds. The light sensor was the shortest at 25 seconds, and the accelerometer was the longest at one minute and 28 seconds. Participants were presented with the questionnaire for a sensor after watching its video. After completing all sensor videos and questionnaires, we followed with a semi-structured interview.

3.1.3 Contrived video demonstration of a series of actions and the associated sensor data (CD-3). Some prior studies utilize interactive demonstrations to improve participant understanding rather than providing a static explanation or description [16, 17, 77, 82]. The added benefit of interactive demonstrations is that they allow participants to engage in parts of the demonstration based on their individual skills and needs [88]. For instance, if multiple applications are presented in

[2]https://simplisafe.com/motion-sensor

the visualization, participants can focus and ask questions about the one they are least familiar with [16].

In this study, to demonstrate the functions of each sensor, a prerecorded video was shown of two researchers interacting in an environment where the sensors were deployed. After playing the video, a researcher explained the data collected by each sensor and related it to the events in the video. These events included turning the lights on and off, walking across the room, picking up an object close to the sensor box, moving furniture, and having a conversation. The data was presented using an interactive visualization (see Section 3.4) of the captured data side-by-side with the video of the activities. Our questionnaire was then administered, followed by a semi-structured interview.

3.1.4 Interactive laboratory demonstration involving quotidian activities and the resulting sensor data (LD-4). Prior studies have engaged participants to interact directly with the devices or perform activities within the scope of a sensor to demonstrate their functionality and observe participants' behavior or responses from these interactions [18, 46, 56, 101]. Visualizing their interaction with these devices or within the scope of these sensors helps them contextualize the function within their activities, which may bring about new viewpoints related to utility and privacy [18, 46, 56].

Participants were instructed to perform a series of activities in the lab while the sensors were actively collecting data. Chronologically, participants were asked to (1) open the lab door and turn on the lights, (2) make a bed, (3) unpack a grocery bag onto a shelf, (4) make tea using an electric kettle, and (5) watch TV with the lights turned off. The collected data was then demonstrated using visualizations described in Section 3.4. Participants were shown what data was captured by each sensor for each activity. Some sensors captured data for only one activity (e.g., radar only had data for unpacking the grocery bag onto a shelf), while others could capture data related to multiple activities (e.g., the PIR sensor captured participants' movement across the room as they performed different activities). Our questionnaire was then administered, followed by a semi-structured interview.

3.1.5 Interactive demonstration including sensed data following a one-week home deployment period (1W-5). Studies that involve home deployments allow participants to interact with devices connected throughout their own home environment [11, 40, 51]. This allows users to navigate utility and data collection concerning their routines, habits, and behaviors in a familiar environment [3, 50, 51].

A sensor box (see Figure 2b) was deployed at each participant's home. The researchers and the participants agreed upon an appropriate location for the sensor box. Participants were asked to describe their daily routine and how often they frequented common areas of their homes. Researchers indicated to the participants that the study objectives favored placement in a location of high use. Most sensor deployments were near a kitchen, living room, or dining area. Participants were asked to maintain a log of activities performed in the vicinity of the sensor box on a sheet provided to them. The collected logs included cooking, dining, washing dishes, watching TV, and having guests over.

A second visit was scheduled within a week of the initial deployment visit. At this visit, data from the sensor boxes was downloaded and visualized on a researcher's laptop while in the participant's home. The activity log was used to recall related sensor data for the noted events. For instance, if the log indicated an activity such as "doing dishes", the data at the time that activity was performed was loaded into the visualization software and presented to the participant as "the 'doing dishes' activity from [day X]". Three to four logged activities were presented to the participants. Our questionnaire was then administered, followed by a semi-structured interview.

Participant ID	Age	Gender	Living Environment	Number of Residents	Sensor Placement
P01	69	Male	House	2	Kitchen
P02	24	Female	Apartment	1	Kitchen
P04	26	Female	House	3	Dining room
P07	26	Male	House	2	Kitchen
P08	45	Female	House	1	Living room
P09	70	Male	House	2	Kitchen
P10	66	Female	House	2	Living room
P11	40	Female	House	3	Kitchen
P12	34	Male	Apartment	1	Living room
P13	20	Male	Apartment	1	Kitchen
P14	24	Male	Apartment	1	Kitchen
P15	25	Female	Apartment	2	Kitchen

Table 2. Demographic and living situations of the participants in our study. The number of residents includes the participants themselves. Participant IDs are not contiguous as P03, P05, and P06 as they did not complete the study.

3.1.6 Interactive demonstration including the resulting data following a one-month home deployment period (1M-6). Prior studies examining end-user perceptions of sensing technologies often reported user habituation to the deployed sensors [19, 103]. Further, while some studies investigated users over multiple months or even years, many in-home deployments were limited to one to two months [94, 103].

A final in-home visit was scheduled four weeks after the sensor deployment (three weeks after the previous visit). Researchers followed the same procedure as *1W-5*, including administering our questionnaire and a semi-structured interview. This marked the end of the participant's involvement in the study, and the sensor box was removed from the participant's home.

3.2 Ethical Considerations

This study was approved by the university's Institutional Review Board (IRB). Participants were informed that the microphone in the sensor box did not store any audio recordings. As part of our recruitment, we also asked any potential participant to obtain verbal consent from all other residents in their homes. All data collected by the sensors were only used for visualization and were stored locally in the sensor box. All collected data in the sensor box were deleted when the box was removed from the participant's home at the end of the home exposures.

3.3 Participants

Participants were recruited through a university-maintained registry of participants. Once a participant expressed interest in our study, their contact details were made available, and a researcher reached out directly to screen and schedule participants. In total, 15 participants from different households enrolled in the study (a full breakdown of demographics and household settings is provided in Table 2). We did not exclude participants based on the number of residents they lived with. As mentioned earlier, we obtained verbal consent from all residents in participant homes.

However, only the participant we recruited was asked to log activities and participate in the interviews and surveys. While the data of other household members (if any) was also likely collected by the sensor box, the activities logged by our participants always included themselves. Moreover, other household members were never the focus of any visualizations we presented. All collected data were destroyed at the end of the home deployment.

One participant withdrew from the study after completing lab exposures (*BL-1*, *VD-2*, *CD-3*, and *LD-4*), citing discomfort with sensors being deployed to their home. Another participant withdrew after the lab exposures for personal reasons unrelated to the study. A third participant withdrew before completing the lab exposures due to feeling unwell. The data from these three participants were not included in any analysis. Participants were paid 150 USD for completing all exposures of the study.

Participants had diverse educational and employment backgrounds. Participants with a technical education background or those employed in the technology industry were excluded from the study since they were more likely to have already a strong understanding of sensing technologies and underlying data. This study focused on *non-expert* users of IoT devices rather than on *experts*. We defined an *expert* as any user with an educational or career background in information technologies. Regarding the demographics of our participants, six identified as male and six as female. Participant ages ranged from 20 to 70 years, with a mean of 39 and a median of 30. Participants exhibited varying degrees of familiarity with the sensors depending upon whether they owned a device with one of these sensors or, in general, were aware of it. For instance, most participants were familiar with the microphone sensor because it is used in everyday devices, including mobile phones.

3.4 Sensor and data visualization

The study used six sensors: an accelerometer (Adafruit LIS3DH Triple-Axis Accelerometer, movement/vibration sensor), a light sensor (SI1145 Digital UV Index / IR / Visible Light Sensor), a microphone (Mini USB 2.0 Microphone), PIR (Adafruit Breadboard-friendly Mini PIR Motion Sensor with 3 Pin Header), radar (Acconeer XE132 Dev Board), and a thermal camera (AMG8833 IR Thermal Camera Breakout). The choice of these sensors was based upon the review of related work (see Section 2) and an assessment of the sensors most commonly used in general-purpose sensing techniques [52].

One notable sensor missing from the study is an RGB video camera. While recent smart-home applications have started using computer vision approaches, they have focused on elder- and life-care applications where privacy considerations are arguably different from those of general-purpose sensing. It was an intentional choice not to include an RGB camera. This decision is supported by arguments presented in prior work, which stated that *cameras have been widely studied and recognized for their high level of privacy invasion and social intrusiveness and thus carry a heavy deployment stigma. This has hindered their use in many environments ripe for sensing, such as homes, schools, care facilities, industrial settings, and work environments. In this work, we show that we can achieve much of the same sensing versatility and accuracy without the use of a camera* (Laput et al. [52]).

Sensing using a smartphone has also garnered much interest from the research community in the last few years, where streams of sensor data from smartphones have been utilized for tasks such as modeling user attention [74] and generating real-time recommendations [21]. While a smartphone encompasses the majority of sensors we studied in this work, we argue that phones are associated with people rather than with spaces, as most people carry them wherever they go [31]. Further, because most people already have significant smartphone exposure due to everyday usage, they already have perceptions related to its usage context. For instance, P14 in our study mentioned during one of the interviews, *"I feel like my cell phone gives somebody way more information than*

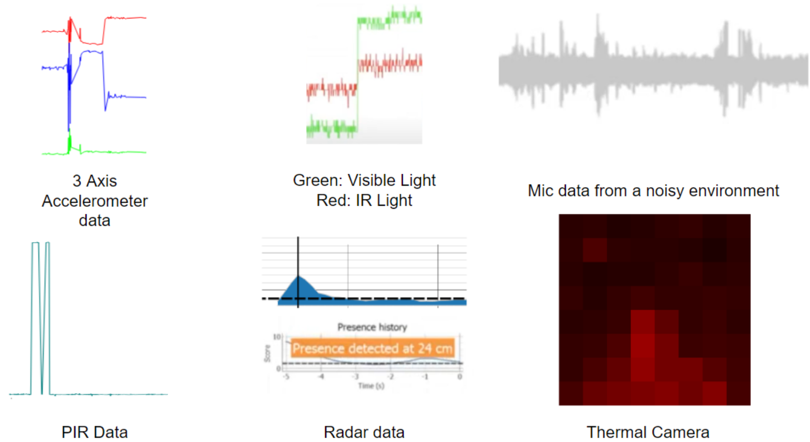


Fig. 3. Figure illustrates the visualizations of sensed data shown to participants. **Accelerometer:** Shows the orientation of the box. **Light:** Shows the intensity of light hitting the sensor. The spike in the graph indicates a sudden increase in light, which is due to lights being turned on. **Microphone:** Shows the amplitude of surrounding noise; larger spikes correspond to louder noises. **PIR:** Binary value showing when motion is present, with a high value indicating motion. **Radar:** Shows the distance to the nearest object in front of the sensor in cm. **Thermal Camera:** Shows the temperature of objects in front of the camera; brighter red indicates warmer objects.

how often I open and close the fridge". In this study, we wanted a unique sensing platform without any usage context and biases from existing devices, so we created our own sensing box.

For *CD-3* through *1M-6*, participants were shown the data values collected by the sensors (accelerometer, light sensor, microphone, PIR, radar, thermal camera). These data values were presented to the participants as plotted on a graph with respect to time (except thermal camera) without any algorithmic interpretation or processing. All the sensors collected data at a frequency greater than or equal to 1 Hz. The data from each sensor was displayed using either a graph or a thermal camera feed, as shown in Figure 3. When the graphs were presented to the participants, they were provided an explanation of the data by interpreting the data represented in the visualizations. All data visualizations were generated the same way and were identical across exposures that used the visualizations in Figure 3. The visualization software used was developed in Python.

3.5 Analysis

An automated transcription service was used to transcribe all interviews. Manual edits were made wherever needed to fix transcription errors. An inductive thematic analysis was performed on interview transcripts [14]. An online collaborative documentation software was used to create and categorize codes. All of the research team was involved in the coding process. We initially independently coded 6 of the 12 participants. Each team member then coded the transcripts coded by others and noted and compared the codes to identify disagreements. All identified disagreements were discussed amongst the team until an agreement was reached. The remaining six interview transcripts were then analyzed and coded independently. The resultant codes were then categorized into themes and sub-themes during multiple discussion sessions among the research team. The final themes of the coding process were (1) Explaining the rating shifts, (2) Acute reorientation can impact ratings, (3) Acceptance was often qualified, (4) Perceived utility impacts participant

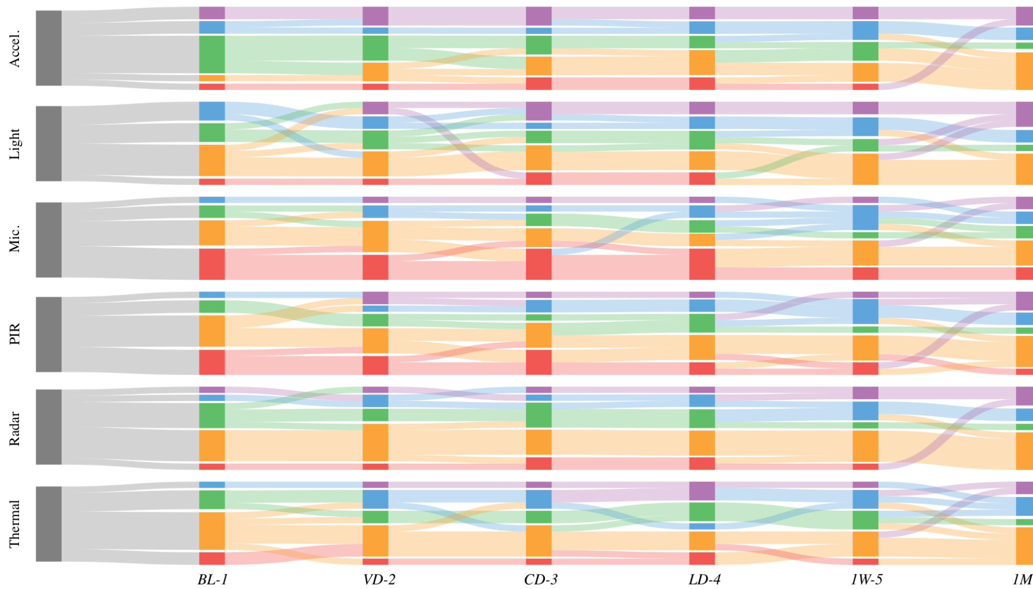


Fig. 4. Comfort ratings are shown as Sankey diagrams for each sensor type through each exposure. Colors are ordered to rating; red: very uncomfortable, orange: somewhat uncomfortable, green: neutral, blue: somewhat comfortable, purple: very comfortable. The diagrams visualize movement in ratings between each exposure.

comfort, and (5) Fading value of data collection notifications in later exposures. All the questionnaire responses were hand-transcribed into a spreadsheet. The variations or changes in ratings were then linked to participant interview responses.

4 RESULTS

Analysis of questionnaires and interview data found meaningful variation across sensor type *as well as* over different exposures. We first summarize key questionnaire responses and then situate our observations within the thematic analysis results.

4.1 Questionnaire and Interview Responses

Participants provided ratings of comfort and utility for each sensor at each exposure using a Likert scale. We used Sankey visualizations to demonstrate how participants' questionnaire responses shifted as they moved through different exposure points. Prior work has demonstrated that Sankey diagrams are effective at visualizing the "flow" between various states or processes [34, 80]. In our particular setting, there is a fixed number of participants at each exposure, with the section in between representing the "flow" or changing ratings. Figures 4 and 5 visualize reported comfort and utility ratings across the exposures experienced in our study. Similarly, Figure 6 visualizes notification preferences across exposures. All three visualizations vividly represent three key findings from this data collection. First, the ratings for each sensor technology in each exposure (visualized as individual stacked color columns) varied between participants, indicating that participants' perceptions varied for each specific technology at each level of exposure. Second, the ratings across sensor technologies in a single exposure (visualized as stacked color columns for all sensor types in a given exposure) varied between participants, indicating that participants' perceptions varied across technologies at each level of exposure. Third, the ratings across exposures for each technology

Sensor Type	*BL-1* (μ)			*VD-2* (μ)			*CD-3* (μ)			*LD-4* (μ)			*1W-5* (μ)			*1M-6* (μ)		
	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.
Accel.	3.75	3.25	3.00	4.50	3.17	2.42	4.33	3.00	2.08	3.58	2.83	2.42	3.50	3.17	1.75	3.83	3.17	1.75
Light	2.67	2.67	2.83	3.83	3.00	2.08	3.75	2.92	1.75	3.50	2.92	1.67	3.25	3.17	1.67	3.25	3.42	1.50
Mic.	2.33	1.92	3.67	3.33	2.25	2.92	3.42	2.17	2.08	3.50	2.33	2.33	3.08	2.83	1.92	3.42	2.83	1.75
PIR	2.83	2.00	3.33	3.67	2.58	2.33	3.17	2.33	2.25	3.33	2.67	2.25	3.00	2.83	1.75	3.50	3.08	1.75
Radar	3.67	2.67	3.33	4.08	2.67	2.33	4.08	2.58	2.92	4.08	2.67	2.17	3.42	3.00	1.75	3.58	3.17	1.50
Thermal	3.08	2.25	3.50	3.08	2.83	2.67	3.33	2.83	1.92	3.42	3.00	1.75	3.17	2.92	1.83	3.25	3.08	1.50

Table 3. Mean scores of participants on 5-point Likert questions asking about utility, comfort, and notification frequency.

Sensor Type	*BL-1* (σ)			*VD-2* (σ)			*CD-3* (σ)			*LD-4* (σ)			*1W-5* (σ)			*1M-6* (σ)		
	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.	Utility	Comfort	Noti.
Accel.	1.36	1.14	1.54	0.80	1.34	1.51	0.98	1.48	1.62	1.16	1.40	1.68	1.31	1.27	1.22	1.47	1.34	1.22
Light	1.07	0.98	1.70	0.94	1.28	1.31	1.06	1.51	1.22	1.24	1.38	1.23	1.22	1.19	1.07	1.48	1.38	1.00
Mic.	1.07	1.00	1.56	1.23	1.36	1.44	1.51	1.34	1.51	1.24	1.44	1.56	1.16	1.34	1.24	1.31	1.40	1.22
PIR	1.47	0.95	1.56	1.23	1.44	1.37	1.40	1.37	1.60	1.37	1.23	1.48	1.13	1.34	1.06	1.45	1.44	1.22
Radar	1.23	1.07	1.50	1.24	1.15	1.37	1.24	1.16	1.24	1.24	1.23	1.53	1.24	1.35	1.22	1.31	1.34	1.00
Thermal	1.24	0.87	1.24	1.24	1.19	1.50	1.15	1.19	1.24	1.24	1.48	1.22	1.11	1.16	1.03	1.29	1.24	0.90

Table 4. Standard Deviation of participants on 5-point Likert questions asking about utility, comfort, and notification frequency.

(visualized as the Sankey flows for each technology) varied between participants, indicating that exposures themselves had influence over ratings.

We note to the readers that non-parametric statistical tests did not find significant results across exposure or sensor. Significant results were found across users (as expected, given the findings of prior work). Table 3 and Table 4 report the means and standard deviations observed. The large variances represent the data's diversity of opinion and sentiment. We believe it also argues that increasing our study size would likely not produce a statistically significant result across exposures or sensors. We present our findings within the context of these highly dynamic results.

4.2 *Participants were able to explain most changes except...*

After the questionnaires were complete, semi-structured interviews were used to allow participants to reflect on changes in their ratings for each technology. When a rating changed, participants were given the opportunity to explain why they changed their rating compared to the prior exposure level. Participants were provided with their current and prior ratings as part of the prompt. This process led to 720 opportunities (12 participants × five exposure transitions × six sensor technologies) for a change in comfort and utility ratings (× 2). Overall, 271 changes were observed. These changes are shown in context in Figures 4 and 5 and summarized in Table 5. In the latter table, columns represent exposure levels, rows represent the degree of change in rating from the prior exposure level quantified as the number of scale points changed, and cells represent the count of changes observed for each exposure/degree pairing. For example, we observed that five comfort and seven utility ratings increased by two scale points between *BL-1* and *VD-2*.

The participants could not explain twenty-four out of these 271 changes. For example, when P10 was asked to explain why their comfort rating for the accelerometer went down, they responded: "*I don't know maybe why it went down, maybe it was just an arbitrary answer.*" P11 was asked a similar question about a light sensor rating: "*I don't know why. I'm sorry. I was honestly thinking something like when I watched that, but I don't know. I don't know why.*"

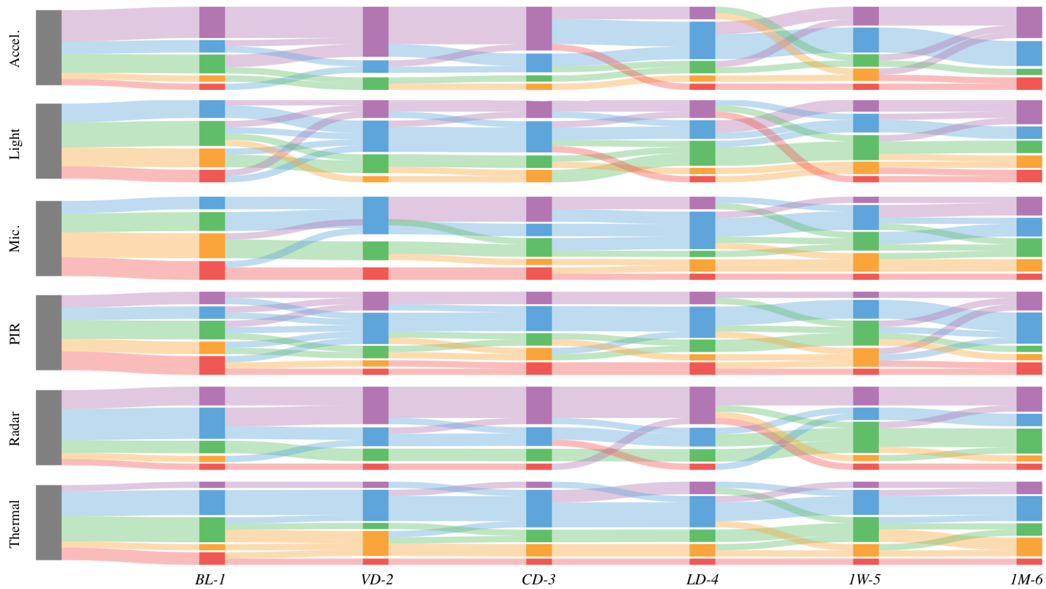


Fig. 5. Utility ratings are shown as Sankey diagrams for each sensor type through each exposure. Colors are ordered according to participants' ratings to the question: "[sensor data collected] would be beneficial to me"; red: strongly disagree, orange: somewhat disagree, green: neutral, blue: somewhat agree, purple: strongly agree. The diagrams visualize movement in ratings between each exposure.

Some participants even contradicted themselves when explaining their changes from prior ratings. For example, when one participant was asked why they felt less comfortable than before, P13 responded: "*I'm more comfortable than [before]*", contradicting their questionnaire response in the process. Many participants failed to answer direct questions in other ways, such as simply agreeing that the change took place, giving a meandering argument that failed to answer the question, or some other form of a non-answer. For example, when P01 was asked why they changed their response from "Maybe allow" to "Allow," their response was simply a clarification of their current stance on the question and not an explanation of the change: "*I'd allow it, period.*" Out of 271 instances of change in comfort or utility, ten resulted in a non-answer when the participant was asked to explain the change.

The observation that many changes were small (i.e., changes of a single Likert point in either direction) may provide a clue to explaining participants' inability to explain rating changes. These small changes could indicate that these participants were on the fence between two points on the Likert scale, struggling to firmly place a rating at any given time. Another possible explanation is that the ratings reflect subconscious changes brought on by familiarity with the sensors over time. Towards this interpretation, P04 commented that "*I was a little nervous towards the beginning because I wasn't sure how it would work. I guess I kind of figured out how it worked, and then, over time, I became more comfortable with it, and I wasn't bothered.*" The above possible explanations do not justify cases where a participant could not explain larger changes in sentiment (i.e., two or more scale points). Four out of 24 unexplained changes were a change of 2 or more points on a 5-point Likert scale.

Change	*BL-1* to *VD-2*		*VD-2* to *CD-3*		*CD-3* to *LD-4*		*LD-4* to *1W-5*		*1W-5* to *1M-6*	
	Utility	**Comfort**	**Utility**	**Comfort**	**Utility**	**Comfort**	**Utility**	**Comfort**	**Utility**	**Comfort**
+4	**1**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**3**
+3	**5**	**2**	**0**	**0**	**0**	**1**	**1**	**0**	**1**	**3**
+2	**7**	**5**	**1**	**2**	**1**	**0**	**1**	**3**	**5**	**1**
+1	**21**	**13**	**9**	**8**	**9**	**9**	**10**	**19**	**11**	**6**
0	**34**	**45**	**48**	**46**	**45**	**57**	**40**	**43**	**44**	**46**
-1	**4**	**6**	**12**	**14**	**13**	**5**	**7**	**7**	**10**	**7**
-2	**0**	**1**	**2**	**1**	**0**	**0**	**9**	**0**	**0**	**6**
-3	**0**	**0**	**0**	**0**	**2**	**0**	**2**	**0**	**0**	**0**
-4	**0**	**0**	**0**	**1**	**1**	**0**	**2**	**0**	**0**	**0**

Table 5. Shows the changes in comfort and utility ratings after exposure transitions. For example, the 21 in the *BL-1* to *VD-2* utility column represents 21 cases where participants' utility ratings increased by 1 point in exposure *BL-1* to *VD-2*. Noteworthy changes are the increase in comfort and utility between *BL-1* and *VD-2* and the decrease in utility between *LD-4* and *1W-5*.

Sensor Type	*BL-1* to *VD-2*				*VD-2* to *CD-3*				*CD-3* to *LD-4*				*LD-4* to *1W-5*				*1W-5* to *1M-6*			
	Utility		**Comfort**		**Utility**		**Comfort**		**Utility**		**Comfort**		**Utility**		**Comfort**		**Utility**		**Comfort**	
	↑	↓	↑	↓	↑	↓	↑	↓	↑	↓	↑	↓	↑	↓	↑	↓	↑	↓	↑	↓
Accel.	5	0	2	1	1	3	1	3	0	6	1	1	3	2	4	0	2	1	1	3
Light	8	1	3	1	1	2	3	2	3	4	1	1	4	3	3	1	2	3	2	1
Mic.	8	1	4	1	4	2	2	3	3	2	1	1	2	3	6	1	5	1	2	3
PIR	7	1	4	0	0	5	1	4	2	1	4	0	2	2	3	2	4	2	3	2
Radar	4	0	2	1	1	1	2	3	1	2	1	0	2	4	4	0	2	1	1	1
Thermal	2	2	8	1	3	1	1	1	2	1	2	2	2	3	3	2	3	2	4	3

Table 6. Summary of rating changes in utility and comfort for each exposure. Here, the cell value represents the number of participants whose ratings changed for a given sensor.

4.3 Acute reorientation can impact ratings

The study controlled how technologies were presented to participants through different levels of exposure. The study, however, did not control participants' existing knowledge, understanding, and biases around specific technologies. We presumed that these existing experiences would likely dominate and regulate participants' perceptions and ratings of different sensors. Interestingly, we found that the exposures were quite influential in reorienting participants' perceptions of the technologies, particularly around their use, utility, and comfort, as discussed below.

4.3.1 Convincing effect of application description videos. One of the exposures where we saw multiple positive perception shifts in ratings of utility and comfort was *VD-2* (see Table 6). While *BL-1* relied on participants' prior experiences and biases toward the presented sensors, *VD-2* introduced these sensors as commercial devices or components of a commercial product. For instance, after watching the video for the microphone sensor, which presented the sensor inside a smart speaker (Amazon Echo Dot), the utility ratings of eight participants went up. In this case, participants' perception of utility was seemingly affected by their own experience using the presented product or through the uses presented in the video. P2, when asked about their utility rating going up for the microphone, mentioned that they already own the device and find it useful: "*Yeah, I mean, I use one. I mostly just use it to play music, but I use one in my house.*" Multiple use cases presented in the videos also helped participants' perceptions of the sensor. For instance, P12 raised their utility rating for the PIR sensor after watching the video, "*I think it was good that it was more informative, made me realize that, yes, there are multiple benefits, not just one benefit for that.*" P14 had a similar response as they realized PIR could be used in motion sensors, "*Sorry, when I was thinking of the PIR initially, it was not like a motion sensor capacity. I didn't even really connect the two. But when I found out it is a motion sensor, I thought of something more like a light detector that works by detecting a change. So when thinking in the motion sensor capacity, I think there is an increased usage potential.*"

Linking sensors to products also impacted participants' comfort with these devices. For instance, P13 pointed out that the microphone on smart speakers listens for commands rather than recording private conversations. P13:"*I'll be comfortable if it's like the Alexa mini where the microphone is receiving my commands about something that I'm seeing instead of a microphone that's recording a conversation.*" Product features mentioned in the videos also affected participants' comfort with some sensors. For instance, P14 pointed out that the easy turn-off controls presented in the PIR video helped with any privacy concerns related to tracking movement: "*Being able to see that use case was, I think, helpful and knowing that it can be limited. And so thinking about it in a limited space, and turning it on and off when I need to was, I think, better than just thinking about it always being on and seeing everything. So I think in a more limited case like that, I would be more willing to have something like that*".

4.3.2 Difficulty in connecting data to utility in later exposures. Participants were presented with visualized sensed data starting with *CD-3*. With this and subsequent exposures, participant sentiment on utility declined (shown in both Figure 5 and Table 6). For instance, when reflecting on the utility of the light sensor *1W-5*, P08 mentioned that the data is not of any particular use for them: "*Unless you put it in a product or display it in a way that makes sense. Graphs mean nothing to me. I guess what I meant was if you can show me how it can be useful. But just seeing it on a graph means absolutely nothing to me. And it's not beneficial.*" Lack of perceived utility was also linked to some participants' increased comfort ratings. Following their earlier comment, when asked about their comfort rating for the light sensor increasing in *1W-5*, P08 elaborated it was "*because the graph doesn't really show anything other than a graph.*"

4.3.3 Exposure to some sensors at home can increase comfort. While it was challenging for participants to think of new applications or use cases for various sensors in later exposures, a change in comfort ratings after in-home deployment was observed. Multiple participants reported higher comfort levels in the first at-home exposure compared to the lab exposures. Specifically, Table 6 shows that six participants' comfort ratings went up for the microphone sensor, four participants' comfort ratings went up for the radar, and 4 participants' comfort ratings went up for the accelerometer. P14 attributed this to a better understanding of the sensor and its placement in a familiar environment, i.e., their home. "*Originally, I was uncomfortable with it because I imagined it being more of a video recording device of some sort. And then I saw the data in the lab, and it's more like a yes or no sort of thing, and that made me more comfortable, and I think seeing it in my own home again made me just a little bit more comfortable there. If somebody else had that data, it doesn't really show you much without context, and so for me, it's like, whatever.*" Similarly, P01 mentioned that the sensor box blended into their home environment, lowering their concern. Although they also mentioned that participating in the study improved their awareness about data collection from other devices they own, *"So now I think it becomes just a part of the house, to be honest. It's kind of*

Sensor Type	BL-1		VD-2		CD-3		LD-4		1W-5		1M-6	
	Utility	Comfort	Utility	Comfort	Utility	Comfort	Utility	Comfort	Utility	Comfort	Utility	Comfort
Accel.	0	0	1	0	1	0	0	0	1	0	0	1
Light	0	1	0	0	0	0	0	0	0	0	0	0
Mic.	0	1	0	5	0	2	0	1	0	1	0	3
PIR	0	1	2	0	0	0	1	1	0	0	0	1
Radar	0	0	0	1	0	0	0	0	0	0	0	0
Thermal	0	0	0	0	0	1	0	0	0	1	1	1
Total	0	3	3	6	1	3	1	2	1	2	1	6

Table 7. Shows the number of times a participant mentioned they had caveats to the sensing technologies. These counts are broken down by exposure level and sensor type.

like until I talked to you guys, I never thought much about the HomePod, the Siri thing, or Alexa until I started thinking about how that's one of the few items that actually sends information out of our house. Automatically, so to speak, versus I mean, I guess my computer's doing that, right, because it's in the middle of the night it updates itself, and that's all right". These observations additionally point to the importance of personal context when it comes to decision-making around sensing devices.

4.4 Acceptance of technologies is often qualified

Participants expressed many caveats when they provided and described their comfort ratings (Table 7). Some stipulations were relatively minor and tied to how the participants believed they could benefit from the sensors. As a result, the type of technology impacted how utility and comfort were perceived. For instance, several participants (P02, P07, P12, P13) were wary of the PIR sensor as it could detect movement in a given space. Consequently, P02 qualified their acceptance by limiting their potential usage of the devices to security: "*Yea, I think I'd allow [PIR sensors] in a certain context if it was a specific device. And I guess motion sensor for security.*"

Other participants' comfort depended on broader concerns about how personal data should be collected. Participants P01, P08, P13, and P14 stated that they would only be comfortable with data collection if it were made transparent. P01 stated "*I want to be told. But if I'm told, I'm probably going to be okay with that. If I'm not told, that sounds sneaky to me. If I buy a consumer device and it's hooked up to the internet, they should at least tell me that they're collecting information, and I can make that decision.*" P12 echoed the sentiment of wanting to be the arbiter over what and how data was collected: "*Yeah, transparency and also control. So yeah, I want my data to be stored based on what I want to control. If I want it to be shared for my benefits, I would like to be notified, or I should be made aware and decide which benefits I need.*"

Financial compensation was another stipulation. P08 acknowledged that companies could gather private information. Despite these concerns, P08 accepted data collection on the condition that they are compensated: "*Sure, you can spy on me all day from companies, you know, this is what the company would pay me for it or compensate me in some way you're not getting private information for free. No way. Companies have billions of dollars, and this information is priceless, and they need to pay for it.*"

Stipulations also varied throughout the exposures. Participants expressed more caveats in the initial lab exposures centered on how the sensor data would be used and how that usage would benefit them. However, after experiencing several exposures, participants initially became less hesitant about the sensors. Indeed, 10 of the 12 participants voiced concerns and qualifications regarding the sensing technologies at some point during the lab exposures, but only 3 of the 12 still qualified for their acceptance of the technologies by the end of the short home deployment. However, after the final extended home deployment, 6 of the 12 participants voiced their concerns again. These participants who still voiced objections echoed similar concerns from previous exposures. These participants expressed concerns about being unaware of what third parties could or would do with their data. As a result, regardless of how the data was shown to them, they were dissatisfied if third parties had access to their data. P12 stated that they wanted an "*explanation about what the data is, how it's been collected, and what the utility of storing it or giving it to the third party is made.*" These concerns are not unique or novel to our study. Many are addressed (in part) by several regulatory acts, such as the European Union's GDPR [27] and the California Consumer Privacy Act [15]. These acts aim to codify into law, among other rights, the right to know what data is collected and who is collecting it.

4.5 Absence of perceived utility triggers divergent sentiment on comfort

Participants' utility ratings for the sensor technologies are summarized in Figure 5 over the series of exposures. Many of the demonstrated technologies did not have obvious utility to the participants, even when the data was presented in combination with participants' in-home behaviors. When we asked about comfort in these technologies, responses largely fell into two categories.

In the first category, participants indicated an increase in comfort as lack of utility reinforced a perspective that the data were benign; participants often reasoned the data from the sensor technology was not informative enough or they were not the type of person to use. For instance, P08 felt more comfortable due to the low utility of the microphone sensor: "*If it is just collecting doors opening and closing and not conversations, there's no harm in that door sounds, TV sounds, window sounds, dog barking, whatever sounds, that is not useful to me.*" P14 even rationalized acceptance through ambiguous potential use: "*Just seeing the data, it is not super useful without some context as to what it's for. But I think there are some use cases that could be beneficial for using it.*" After *VD-2*, P09 rationalized acceptance after recognizing a microphone sensor was already in use in his home, stating that his wife uses voice commands to set up alarms on her phone.

In the second category, the lack of utility elicited privacy concerns, increased skepticism of the technology, and decreased comfort with the technology. For instance, P08's comfort decreased because they felt that thermal data was "useless": "*I think that's completely useless. I don't care to know myself when I'm cooking.*" P02, when asked why they were very uncomfortable with the data collection, responded: "*Um, yeah, I feel like I still don't know what the data would be used for to benefit me. So I guess I wouldn't want to... I would feel uncomfortable if someone was collecting it and not telling me why.*"

Interestingly, sometimes participants' sentiments fell into both rationalization categories. P09's rationalization of his wife's use of microphones in the home (above) contrasts with his assessment of sensor data after *1M-6*: "*Seeing the visual with the chart, it just seemed almost pointless. And so I would be less comfortable for that, that data to be collected. But seeing the visualization as well as the graph, it certainly changed my feeling about that collection of data there.*"

4.6 Value of notification of data collection fades with exposure

In addition to asking participants about utility and comfort after each stage of exposure, we also asked about participants' preferences related to notification frequency for data collection from these sensors. We noticed an interesting pattern where multiple participants in early exposures indicated wanting to be notified each time data collection took place. This can also be observed in Figure 6 as a prominent number of participants answered *'Strongly Agree'* to the question *"I would like to be notified every time this data collection occurs"*, especially for the microphone sensor.

As explained by the participants, the initial desire for frequent notifications was related to awareness of data collection and the presence of these devices and sensors. For instance, P8

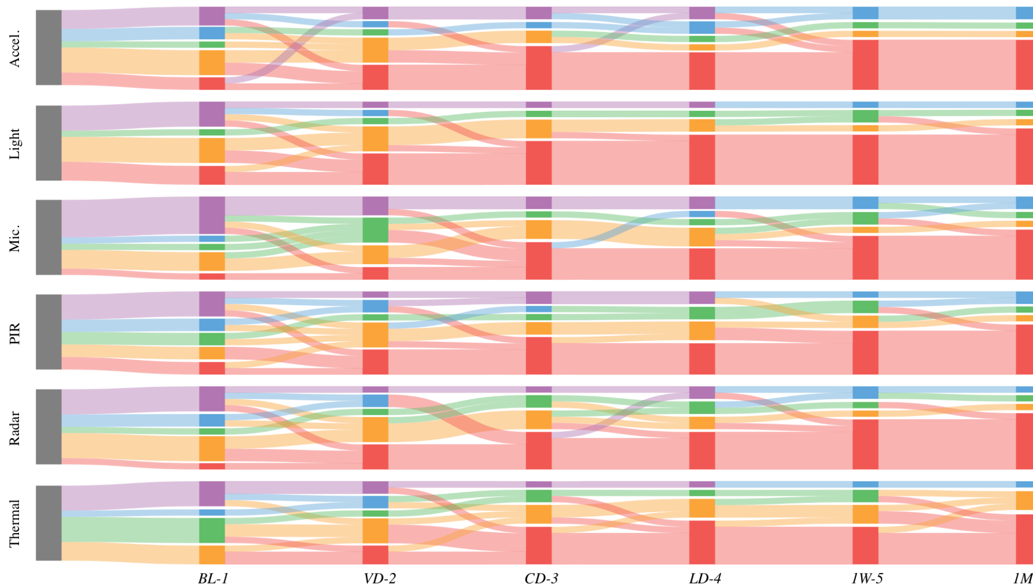


Fig. 6. Notification ratings are shown as Sankey diagrams for each sensor type through each exposure. Colors are ordered according to participants' ratings to the question: "I would like to be notified every time this data collection occurs."; red: strongly disagree, orange: somewhat disagree, green: neutral, blue: somewhat agree, purple: strongly agree. The diagrams visualize movement in ratings between each exposure.

suggested that, in the context of a microphone sensor, notifications would help serve as a reminder of data collection by these sensors: "*You might forget, you want to know, because there are some things like they would never ever need to know, like, if you are reading your social security number, they don't need that. I mean, that's a private number that's only for specific uses. And if you forget and start saying it to someone or reading it because you're on the phone with someone or whatever, you might forget. So, you know, you're gonna forget if it's on all the time, so you should be notified definitely every time.*"

As the exposures progressed, the frequency of *'Strongly Disagree'* responses increased. This is denoted by the red in Figure 6. In contrast, the purple responses *'Strongly Agree'* decreased to the point that by *1W-5*, there were no purple responses for any sensor. When questioned about the rationale behind decreased notification frequencies, participant reasoning was often based upon the type of device and acclimatization to how that device would function in a specific context. For instance, P13 imagined being overwhelmed by notifications if they have multiple sensors in their home: "*Because you interact with lights every day, it would just be annoying if you get notified every time.*" P02 states, "*Yeah, it was just one of those things. I feel like it's constantly being active, so I wouldn't want it to be notified. So it would just be annoying.*" P10 expressed similar exasperation, stating "*I don't know that being notified would help me in any way. And I am definitely suffering from notification fatigue. Alexa notifies [me], my phone notifies me about things, the cameras outside are constantly notifying me of, like, leave me alone.*"

In addition to contextual habituation, the realization of too many notifications also emerged after participants established a greater understanding of the data collected. For instance, P14 mentioned after *1W-5* that notifications about data collections are not helpful for them, and there is potential for too many notifications: "*seeing some of the data made me realize how much of it there is. And*

I just don't think for me being notified about the data collection is useful. I think it would be more utilized in linking to other devices or alerting me when there's something wrong." Knowing what the data looks like in later exposures also affected participants' notification frequency preferences. P15 pointed out during *1W-5* that looking at what data is collected made them more comfortable with data collection resulting in not wanting frequent notifications about it: "*Once I know what kind of data it is, and I know it's no longer something that can tell the manufacturer or whoever is collecting information about me, I feel more comfortable.*"

There were some notable exceptions to lack of notification utility in later exposures, as seen in Figure 6, where a few blue responses (*'Somewhat Agree'*) appear in *1W-5* and *1M-6*. In cases where the participants established potential security or safety applications of a sensor, they preferred to be notified often, no matter which phase of exposure they were currently in. This was not limited to a single sensor; instead, participants identified safety applications for multiple different sensors. For instance, P08's notification frequency preference dropped after the *LD-4* exposure for most sensors except radar, where they recognized potential safety applications: "*I put if it's for a safety thing, or if you're specifically using it for notification, then obviously, yes, you want to be notified if that's what you're using it for. I mean, if you bought it specifically for notification purposes, and yes, you would want it to work every time.*" P11 suggested using notifications for identifying anomalies that raise safety concerns, such as detecting when the refrigerator door is left open using the accelerometer sensor. P10 wanted frequent notifications for the microphone sensor to detect human presence at odd hours in their home "*if it's recording a whole conversation, I would definitely want to know every time.*"

5 DISCUSSION

Our study was designed to understand user perceptions of in-home IoT sensors without directly tying those sensors to a specific application or set of applications. Given our proposed framing, this was an explicit decision that general-purpose sensing approaches are emerging and present a new design challenge where sensing devices and their related applications will not be paired or even tightly coupled. The approach allowed us to explore a sensing-first orientation to understanding user assessments of comfort and utility. Our study results showed that users struggle to connect underlying sensor data to the utility of specific applications. Our work also extends prior findings by showing how users' understanding evolves and shifts perceptions of comfort and utility over different levels of engagement and with different sensing techniques. For instance, with regards to different sensor types, [11] explored exposures *BL-1*, *1W-5*, and *1M-6* with microphone and camera sensors. Their work showed that participant attitudes remained positive over time, affecting their acceptance and intention to continue using the robots. However, in Section 4.4, we noted that acceptance of technologies is often qualified, with these stipulations also varying across exposure and sensor types. Our results also demonstrate how exposure impacts participant perceptions of utility. While [109] found participants perceived high utility across four sensors in a single exposure (*VD-2*), we demonstrated that participant sentiment on utility declined in later exposures (see Section 4.3.2).

With single-purpose sensing, the research community has explored mechanisms to inform and provide end-user data collection control as an application use decision. For instance, if a user becomes uncomfortable with the data an application is leveraging, they can disable or alter the function of the single-purpose sensing device to match their comfort and utility expectations [102]. These mechanisms are unavailable with general-purpose sensing since a single sensor may provide data to several applications. Our study showed that perceptions around specific data and their use could influence overall comfort with a general-purpose IoT device. Further, these changes are not uniform across device types. This suggests that applications that leverage data from general-purpose sensing sources will need to be managed or coordinated on behalf of the user, perhaps similar to how user-level controls for sensor data have evolved over many generations of mobile computing platforms. We present several design implications specific to a shift to general-purpose sensing in Section 5.1. Broadly, these implications argue the need for tools that allow users to better understand and have agency over the associations between data sources and data use by applications and to maintain awareness of how those connections change over time and through different use conditions.

The findings of our study are tied to the specific exposures investigated. These data collection points were selected and designed to reflect the typical milestones a user would encounter and experience when learning about and choosing to use smart home IoT technologies. We argue these are important points to consider when designing a user experience from the first discovery of the application's existence to its early use in the home. Indeed, prior work also heavily informed the selection of exposures (see Table 1), allowing our findings to connect and weave across established findings. However, the exposures chosen do not cover a lifetime of use nor all of the specific and personal interaction milestones a user may encounter. Studies that look at use over a longer arc are necessary, but just as much, studies that investigate changes with much more focused arcs are also necessary. For instance, it is likely that perceptions of utility and comfort change rapidly in the early hours to minutes of use with a novel application and likely (based on our findings) shift uniquely across sensing mechanisms. Multiple, multi-dimensional perspectives will be necessary to fully understand perceptions of utility and comfort with general-purpose sensing.

5.1 Design Implications

5.1.1 Opportunities for intervention. Throughout the study, participants' perceptions of sensor utility and comfort shifted as they went through different exposures. While the effect of the *VD-2* on the perception of the utility was largely positive across sensing modalities for all users (Section 4.3), other exposures led to both positive and negative variations based on the participants' personal contexts. This indicates that these exposures represent essential and meaningful intervention points that can be leveraged to engage with users to assess their understanding of device functionality in the context of their own data and usage. Notably, designers should look for significant shifts in exposure—e.g., changes in the device/sensor location, frequency of data collection, or habituation within a particular space—to enable these interventions. Identification and usage of these intervention points could help address the documented overload of notifications experienced by users [24, 25].

5.1.2 Reinforce trust through data usage awareness. In Section 4.3, we noted that bringing technology home helped multiple participants contextualize the sensor to their own environment, which helped with their comfort ratings for these sensors. For a few participants, this was not the case for all sensors, as seen in Figure 4 and Table 5. However, from the figure and the table, we can see that for these participants, their comfort rating went up after the third home visit following the *1M-6* exposure as they further habituated to the sensors. This indicates that there is an opportunity to address user concerns through improved awareness during the initial period of device adoption. One way to address this is through specific application interventions. These interventions should focus on increasing users' awareness of how their data is collected and used, particularly during the first week when the device is at home. For example, personalized video descriptions could be used to showcase what data is collected and the events precipitating that collection. This context could help users make informed decisions surrounding changes to settings or the deployment of sensors. Surprisingly, this level of visibility into the behavior of IoT devices is rarely observed, even from large-scale manufacturers. A notable exception is Apple, which presents data collected as part of its Apple Health research study[3]. In this work, we observed that while participants were often familiar with the device, they were unfamiliar with the underlying data. When they were made aware of what the data entails, it often resulted in improved comfort with and around the device. We also observed that as people learned more about the data, they felt they were more informed about data collection practices for other devices as well (Section 4.3.3). We argue that more device manufacturers should create interventions that present users with a view into their own data.

5.1.3 General-purpose sensing is not necessarily generalized. From Table 6, we can observe that participants' perceptions of different sensor modalities varied at the same exposure level. For instance, when observing the shift from exposure *1W-5* to *1M-6*, we noticed that while the thermal camera saw an uptick in comfort ratings for four participants, the accelerometer saw a drop in comfort ratings for three participants. Similar unpredictable variations can also be observed at other transitions for different sensors. This points to the importance of considering sensor modalities when designing awareness interfaces. There may exist greater sensitivities to certain forms of sensing that may fit into a specific use case. For instance, a user may not perceive a change in the motion sensor reading when having guests over at the same level as when there is a change in the reading of a microphone in the same space. Thus, when designing awareness interfaces for general-purpose sensors that accommodate multiple sensor modalities, it is crucial to consider and highlight differences between them rather than lumping all the data together.

Further, since general-purpose sensing can enable the detection of many types of activities [52] in a given space, designing interfaces that allow selective enabling and disabling of individual sensors on a per-application basis can help balance application performance with user comfort. In Section 4.5, we noted how participants' comfort ratings varied depending on whether they could connect sensor data to an application. This suggests that it would be beneficial to tie specific sensor data to applications when it is presented to the user. For instance, in the case of a smart speaker with recorded audio data, the interface could present the questions the user asked and that got stored and how far back this data retention goes.

5.1.4 Need for trusted mediation to improve user comprehension surrounding data collection. As explained in Section 3.4, we used sensor data visualizations to describe collected data to our participants. Our results indicate that these visualizations alone may not suffice in increasing user understanding regarding the implications of the collected data. This can be observed in quotes from P14 in Section 4.3.3 and P08 and P09 in Section 4.5, where the reflection on their comfort with data collection was solely based on information presented in the visualization without factoring in data processing, such as inferences through data aggregation from multiple sources [52]. Our reasoning for presenting visualizations instead of raw sensed data was the sheer amount of collected data per participant, which sometimes amounted to 100s of gigabytes during the one month of home deployment. While we did try to ensure that the visualizations were comprehensible to the users, it is likely that additional data literacy tools, including visualizations and mechanisms, would need to be individually evaluated for overall efficacy in promoting trust and explaining utility. This work provides unique and novel insights that such tools are likely necessary throughout many engagement experiences with the technology – from early adoption to sustained presence.

5.1.5 Alert users of abnormal data. We noted in Section 4.6 that, in the initial exposures, users indicated a desire for frequent notifications about data collection. For later exposures, participants' desire for regular notifications decreased except for cases where they linked the data collection

[3] https://support.apple.com/en-us/HT210652

notification with an application such as safety and security. Specific desires to understand abnormalities in data (e.g., the thermal camera constantly recording high temperature or motion/speech detected during working hours) were of interest to participants in our study. Depending on sensor type and placement, multiple types of abnormal events can be reported. Helping users understand irregularities or routine deviations could help minimize alert fatigue while providing useful feedback to ensure comfort with general-purpose sensors.

5.2 Limitations and Future Work

The size of our study, particularly with it being performed in one geographic location and in a single Western country, undoubtedly limits the scope of the study's findings and implications. Repeating our methodological approach across broader populations is needed to understand broad societal applicability. Further, the study methodology suffers from self-selection bias; participants decided to enroll in the study upon reading its description, including the mention of deploying sensors at home. Many participants likely did not respond to our study solicitation because they were outright uncomfortable with having a sensor box deployed at their homes. This is a limitation of all voluntary studies and has to be reflected upon when considering broader implications. In addition, several participants withdrew after enrolling in the study, as mentioned in Section 3.3.

As discussed in Section 3.3, our findings were only focused on the recruited participant and not other household members, where interaction between them could have affected our study results [94]. Our focus with this work was on evaluating changes in *individual* perceptions related to general-purpose sensing with progressive exposures. Interaction between other household members and the study participant may have affected their responses during the home exposure points. Further investigation is needed to understand how individual perceptions related to general-purpose sensing are affected by social or interpersonal elements.

Further, as mentioned in Section 3.4, we visualized sensed data values to the participants for exposures *CD-3* to *1M-6*. However, it is possible that the participants may have had limited comprehension of these visualizations or may even infer inaccurate information from them [91], which could explain their perception of the reduced utility of sensed data in these exposures. This highlights the importance of further exploration, refinement, and development of visualizations for general-purpose sensing to communicate processes and data better.

It was a purposeful decision not to focus on any specific, well-defined smart-home applications. We wanted participants to reflect on the sensors and data gathered, not on a particular use case for each of these sensors. This approach has an important limitation; our study observed variations in *perception* of utility and comfort but not necessarily variations in *experienced* utility and comfort. Participant perceptions surrounding utility and comfort were highly variable when looking at the scope of applications possible with the data. Further studies, including the development of new methodological approaches, are needed to holistically understand utility and comfort within the context of general-purpose sensing environments and applications.

This study was conducted over a period of one month, and significant fluctuations in utility and comfort were observed. Our study focused on early engagements, as this is when people form their initial opinions and understanding of the data. Thus, most of our implications focus on this initial engagement and understanding of general-purpose sensing data. However, people's opinions do not stop changing one month into use. This has been shown by the limited work investigating long-term exposure [11, 20].

Finally, our study was not meant to evaluate overall acceptance but rather changes in acceptance over time and through different exposures. Further research is necessary to understand how those changes will impact users who may be further behind on the smart-home adoption curve. While our focus was on individual changes in perception of general-purpose sensing through incremental exposures, power dynamics in the household can further impact the perception of control of smart-home devices [10, 35]. Understanding how power dynamics within the context of a shared home impact perceptions of general-purpose IoT sensing is an important area of future work.

6 CONCLUSION

In this work, we explored utility and comfort with in-home sensing within the context of general-purpose sensing, a paradigm shift from traditional in-home sensing approaches in which a sensor is used explicitly to support a single device or application. As summarized in Table 1, prior work has tended to study user comfort with specific sensors across at most three exposures. Instead, our work represents a more extended and nuanced walk-through of six important exposures drawn from the literature through a longitudinal study to understand how utility and comfort change over time. Our findings suggest that the design for general-purpose sensing may be more complex and nuanced than current insights driven by special-purpose sensing. This work argues that our community needs to design for dynamic levels of comfort and utility, i.e., design systems with constant reinforcement of trust through data awareness. Notably, we need to design for general-purpose sensing that keeps user agency in mind, as our findings suggest that the users can easily be influenced.

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REFERENCES

[1] Fadi Al Machot, Mohammed R. Elkobaisi, and Kyandoghere Kyamakya. 2020. Zero-shot human activity recognition using non-visual sensors. *Sensors* 20, 3 (2020), 825.

[2] Ahmad Alaiad and Lina Zhou. 2014. The determinants of home healthcare robots adoption: An empirical investigation. *International Journal of Medical Informatics* 83, 11 (Nov. 2014), 825–840. https://doi.org/10.1016/j.ijmedinf.2014.07.003

[3] Aloha Hufana Ambe, Margot Brereton, Alessandro Soro, and Paul Roe. 2017. Technology Individuation: The Foibles of Augmented Everyday Objects. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 6632–6644. https://doi.org/10.1145/3025453.3025770

[4] Noah Apthorpe, Yan Shvartzshnaider, Arunesh Mathur, Dillon Reisman, and Nick Feamster. 2018. Discovering Smart Home Internet of Things Privacy Norms Using Contextual Integrity. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 2 (July 2018), 1–23. https://doi.org/10.1145/3214262

[5] Sogol Balali, Ross T. Sowell, William D. Smart, and Cindy M. Grimm. 2019. Privacy Concerns in Robot Teleoperation: Does Personality Influence What Should Be Hidden?. In *Social Robotics: 11th International Conference, ICSR 2019, Madrid, Spain, November 26–29, 2019, Proceedings* (Madrid, Spain). Springer-Verlag, Berlin, Heidelberg, 719–729. https://doi.org/10.1007/978-3-030-35888-4_67

[6] Natã M. Barbosa, Zhuohao Zhang, and Yang Wang. 2020. Do Privacy and Security Matter to Everyone? Quantifying and Clustering User-Centric Considerations about Smart Home Device Adoption. In *Proceedings of the Sixteenth USENIX Conference on Usable Privacy and Security (SOUPS'20)*. USENIX Association, USA, Article 22, 19 pages.

[7] Natã M. Barbosa, Joon S. Park, Yaxing Yao, and Yang Wang. 2019. *"What if?"* Predicting Individual Users' Smart Home Privacy Preferences and Their Changes. *Proceedings on Privacy Enhancing Technologies* 2019, 4 (Oct. 2019), 211–231. https://doi.org/10.2478/popets-2019-0066

[8] Eric Becker, Zhengyi Le, Kyungseo Park, Yong Lin, and Fillia Makedon. 2009. Event-Based Experiments in an Assistive Environment Using Wireless Sensor Networks and Voice Recognition. In *Proceedings of the 2nd International Conference on PErvasive Technologies Related to Assistive Environments* (Corfu, Greece) *(PETRA '09)*. Association for Computing Machinery, New York, NY, USA, Article 17, 8 pages. https://doi.org/10.1145/1579114.1579131

[9] A.R. Beresford and F. Stajano. 2003. Location privacy in pervasive computing. *IEEE Pervasive Computing* 2, 1 (2003), 46–55. https://doi.org/10.1109/MPRV.2003.1186725

[10] Arne Berger, Andreas Bischof, Sören Totzauer, Michael Storz, Kevin Lefeuvre, and Albrecht Kurze. 2019. Sensing home: participatory exploration of smart sensors in the home. In *Social Internet of Things*. Springer, 123–142.

[11] Roberta Bevilacqua, Amedeo Cesta, Gabriella Cortellessa, Alessandro Macchione, Andrea Orlandini, and Lorenza Tiberio. 2014. Telepresence Robot at Home: A Long-Term Case Study. In *Ambient Assisted Living*, Sauro Longhi, Pietro Siciliano, Michele Germani, and Andrea Monteriù (Eds.). Springer International Publishing, Cham, 73–85.

[12] Patrick Boissy, Hélène Corriveau, François Michaud, Daniel Labonté, and Marie-Pier Royer. 2007. A qualitative study of in-home robotic telepresence for home care of community-living elderly subjects. *Journal of telemedicine and telecare* 13, 2 (2007), 79–84.

[13] Andriana Boudouraki, Stuart Reeves, Joel E Fischer, and Sean Rintel. 2022. Mediated Visits: Longitudinal Domestic Dwelling with Mobile Robotic Telepresence. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 251, 16 pages. https://doi.org/10.1145/3491102.3517640

[14] V. Braun and V. Clarke. 2013. *Successful Qualitative Research: A Practical Guide for Beginners.* SAGE Publications. https://books.google.com/books?id=nYMQAgAAQBAJ

[15] PRESTON BUKATY. 2019. *RIGHTS OF CONSUMERS AND OBLIGATIONS OF THE BUSINESS.* IT Governance Publishing, 55–89. http://www.jstor.org/stable/j.ctvjghvnn.9

[16] Daniel J. Butler, Justin Huang, Franziska Roesner, and Maya Cakmak. 2015. The Privacy-Utility Tradeoff for Remotely Teleoperated Robots. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction* (Portland, Oregon, USA) *(HRI '15)*. Association for Computing Machinery, New York, NY, USA, 27–34. https://doi.org/10.1145/2696454.2696484

[17] Daniel J. Butler, Justin Huang, Franziska Roesner, and Maya Cakmak. 2015. The Privacy-Utility Tradeoff for Remotely Teleoperated Robots. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction* (Portland, Oregon, USA) *(HRI '15)*. Association for Computing Machinery, New York, NY, USA, 27–34. https://doi.org/10.1145/2696454.2696484

[18] Kelly Caine, Selma Šabanovic, and Mary Carter. 2012. The Effect of Monitoring by Cameras and Robots on the Privacy Enhancing Behaviors of Older Adults. In *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction* (Boston, Massachusetts, USA) *(HRI '12)*. Association for Computing Machinery, New York, NY, USA, 343–350. https://doi.org/10.1145/2157689.2157807

[19] Nico Castelli, Corinna Ogonowski, Timo Jakobi, Martin Stein, Gunnar Stevens, and Volker Wulf. 2017. What Happened in My Home? An End-User Development Approach for Smart Home Data Visualization. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 853–866. https://doi.org/10.1145/3025453.3025485

[20] Amedeo Cesta, Gabriella Cortellessa, Andrea Orlandini, and Lorenza Tiberio. 2016. Long-Term Evaluation of a Telepresence Robot for the Elderly: Methodology and Ecological Case Study. *International Journal of Social Robotics* 8, 3 (June 2016), 421–441. https://doi.org/10.1007/s12369-016-0337-z

[21] Chia-Chen Chen, Tien-Chi Huang, James J Park, and Neil Y Yen. 2015. Real-time smartphone sensing and recommendations towards context-awareness shopping. *Multimedia systems* 21, 1 (2015), 61–72.

[22] Eun Kyoung Choe, Sunny Consolvo, Jaeyeon Jung, Beverly Harrison, and Julie A. Kientz. 2011. Living in a Glass House: A Survey of Private Moments in the Home. In *Proceedings of the 13th International Conference on Ubiquitous Computing* (Beijing, China) *(UbiComp '11)*. Association for Computing Machinery, New York, NY, USA, 41–44. https://doi.org/10.1145/2030112.2030118

[23] Fuh Kee Chuah and Soo Siang Teoh. 2020. Thermal Sensor based Human Presence Detection for Smart Home Application. In *2020 10th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*. 37–41. https://doi.org/10.1109/ICCSCE50387.2020.9204940

[24] Jessica Colnago, Yuanyuan Feng, Tharangini Palanivel, Sarah Pearman, Megan Ung, Alessandro Acquisti, Lorrie Faith Cranor, and Norman Sadeh. 2020. Informing the Design of a Personalized Privacy Assistant for the Internet of Things. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376389

[25] Jessica Colnago and Hélio Guardia. 2016. How to Inform Privacy Agents on Preferred Level of User Control?. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct* (Heidelberg, Germany) *(UbiComp '16)*. Association for Computing Machinery, New York, NY, USA, 1542–1547. https://doi.org/10.1145/2968219.2968546

[26] S. Coradeschi, A. Cesta, G. Cortellessa, L. Coraci, J. Gonzalez, L. Karlsson, F. Furfari, A. Loutfi, A. Orlandini, F. Palumbo, F. Pecora, S. von Rump, A. Štimec, J. Ullberg, and B. Ötslund. 2013. GiraffPlus: Combining social interaction and long term monitoring for promoting independent living. In *2013 6th International Conference on Human System Interactions (HSI)*. 578–585. https://doi.org/10.1109/HSI.2013.6577883

[27] Council of European Union. 2018. General Data Protection Regulation. https://gdpr.eu/.

[28] Maartje M. A. de Graaf, Somaya Ben Allouch, and Jan A. G. M. van Dijk. 2019. Why Would I Use This in My Home? A Model of Domestic Social Robot Acceptance. *Human–Computer Interaction* 34, 2 (March 2019), 115–173.

https://doi.org/10.1080/07370024.2017.1312406

[29] Flavia C. Delicato, Paulo F. Pires, Thais Batista, Everton Cavalcante, Bruno Costa, and Thomaz Barros. 2013. Towards an IoT Ecosystem. In *Proceedings of the First International Workshop on Software Engineering for Systems-of-Systems* (Montpellier, France) *(SESoS '13)*. Association for Computing Machinery, New York, NY, USA, 25–28. https://doi.org/10.1145/2489850.2489855

[30] Stephen Eick and Annie I. Antón. 2020. Enhancing Privacy in Robotics via Judicious Sensor Selection. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*. 7156–7165. https://doi.org/10.1109/ICRA40945.2020.9196983

[31] Richard Emanuel, Rodney Bell, Cedric Cotton, Jamon Craig, Danielle Drummond, Samuel Gibson, Ashley Harris, Marcus Harris, Chelsea Hatcher-Vance, Staci Jones, et al. 2015. The truth about smartphone addiction. *College Student Journal* 49, 2 (2015), 291–299.

[32] Francisco Erivaldo Fernandes, Guanci Yang, Ha Manh Do, and Weihua Sheng. 2016. Detection of Privacy-Sensitive Situations for Social Robots in Smart Homes. In *2016 IEEE International Conference on Automation Science and Engineering (CASE)* (Fort Worth, TX, USA). IEEE Press, 727–732. https://doi.org/10.1109/COASE.2016.7743474

[33] R. Gross, L. Sweeney, F. de la Torre, and S. Baker. 2006. Model-Based Face De-Identification. In *2006 Conference on Computer Vision and Pattern Recognition Workshop (CVPRW'06)*. 161–161. https://doi.org/10.1109/CVPRW.2006.125

[34] Carl Gutwin, Aristides Mairena, and Venkat Bandi. 2023. Showing Flow: Comparing Usability of Chord and Sankey Diagrams. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 825, 10 pages. https://doi.org/10.1145/3544548.3581119

[35] Tom Hargreaves, Richard Hauxwell-Baldwin, Mike Coleman, Charlie Wilson, Lina Stankovic, Vladimir Stankovic, Jing Liao, David Murray, Tom Kane, Tarik Hassan, and Steven Firth. 2015. Smart homes, control and energy management : how do smart home technologies influence control over energy use and domestic life?, In ECEEE-2015. *ECEEE-2015*. https://strathprints.strath.ac.uk/55060/

[36] Tanja Heuer, Ina Schiering, and Reinhard Gerndt. 2019. Privacy-centered design for social robots. *Interaction Studies* 20 (11 2019), 509–529. https://doi.org/10.1075/is.18063.heu

[37] Peter Hevesi, Sebastian Wille, Gerald Pirkl, Norbert Wehn, and Paul Lukowicz. 2014. Monitoring Household Activities and User Location with a Cheap, Unobtrusive Thermal Sensor Array. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Seattle, Washington) *(UbiComp '14)*. Association for Computing Machinery, New York, NY, USA, 141–145. https://doi.org/10.1145/2632048.2636084

[38] Alexander Hubers, Emily Andrulis, William D. Smart, Levi Scott, Tanner Stirrat, Duc Tran, Ruonan Zhang, Ross Sowell, and Cindy Grimm. 2015. Video Manipulation Techniques for the Protection of Privacy in Remote Presence Systems. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction Extended Abstracts* (Portland, Oregon, USA) *(HRI'15 Extended Abstracts)*. Association for Computing Machinery, New York, NY, USA, 59–60. https://doi.org/10.1145/2701973.2702048

[39] Yasha Iravantchi, Karan Ahuja, Mayank Goel, Chris Harrison, and Alanson Sample. 2021. PrivacyMic: Utilizing Inaudible Frequencies for Privacy Preserving Daily Activity Recognition. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 198, 13 pages. https://doi.org/10.1145/3411764.3445169

[40] Timo Jakobi, Gunnar Stevens, Nico Castelli, Corinna Ogonowski, Florian Schaub, Nils Vindice, Dave Randall, Peter Tolmie, and Volker Wulf. 2018. Evolving Needs in IoT Control and Accountability: A Longitudinal Study on Smart Home Intelligibility. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 4, Article 171 (dec 2018), 28 pages. https://doi.org/10.1145/3287049

[41] Suman Jana, Arvind Narayanan, and Vitaly Shmatikov. 2013. A Scanner Darkly: Protecting User Privacy from Perceptual Applications. In *2013 IEEE Symposium on Security and Privacy*. 349–363. https://doi.org/10.1109/SP.2013.31

[42] Christina Jaschinski, Somaya Ben Allouch, Oscar Peters, and Jan van Dijk. 2020. The Influence of Privacy on the Acceptance of Technologies for Assisted Living. In *Human Aspects of IT for the Aged Population. Healthy and Active Aging*, Qin Gao and Jia Zhou (Eds.). Springer International Publishing, Cham, 463–473.

[43] Li Jia and Richard J. Radke. 2014. Using Time-of-Flight Measurements for Privacy-Preserving Tracking in a Smart Room. *IEEE Transactions on Industrial Informatics* 10, 1 (2014), 689–696. https://doi.org/10.1109/TII.2013.2251892

[44] Margot E Kaminski, Matthew Rueben, William D Smart, and Cindy M Grimm. 2016. Averting robot eyes. *Md. L. Rev.* 76 (2016), 983.

[45] Viktória Kerekešová, František Babič, and Vladimír Gašpar. 2019. Using the Virtual Assistant Alexa as a Communication Channel for Road Traffic Situation. In *Multimedia and Network Information Systems*, Kazimierz Choroś, Marek Kopel, Elżbieta Kukla, and Andrzej Siemiński (Eds.). Springer International Publishing, Cham, 35–44.

[46] Jeffrey Klow, Jordan Proby, Matthew Rueben, Ross T. Sowell, Cindy M. Grimm, and William D. Smart. 2017. Privacy, Utility, and Cognitive Load in Remote Presence Systems. In *Proceedings of the Companion of the 2017 ACM/IEEE*

International Conference on Human-Robot Interaction (Vienna, Austria) *(HRI '17)*. Association for Computing Machinery, New York, NY, USA, 167–168. https://doi.org/10.1145/3029798.3038341

[47] Ella Kolkowska. 2015. Privacy Principles in Design of Smart Homes Systems in Elderly Care. In *Human Aspects of Information Security, Privacy, and Trust*, Theo Tryfonas and Ioannis Askoxylakis (Eds.). Springer International Publishing, Cham, 526–537.

[48] Ella Kolkowska. 2015. Privacy Principles in Design of Smart Homes Systems in Elderly Care. In *Human Aspects of Information Security, Privacy, and Trust*, Theo Tryfonas and Ioannis Askoxylakis (Eds.). Springer International Publishing, Cham, 526–537.

[49] Margaret M. Krupp, Matthew Rueben, Cindy M. Grimm, and William D. Smart. 2017. A focus group study of privacy concerns about telepresence robots. In *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. 1451–1458. https://doi.org/10.1109/ROMAN.2017.8172495

[50] Albrecht Kurze, Andreas Bischof, Sören Totzauer, Michael Storz, Maximilian Eibl, Margot Brereton, and Arne Berger. 2020. Guess the Data: Data Work to Understand How People Make Sense of and Use Simple Sensor Data from Homes. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376273

[51] Hyosun Kwon, Joel E. Fischer, Martin Flintham, and James Colley. 2018. The Connected Shower: Studying Intimate Data in Everyday Life. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4 (Dec. 2018), 1–22. https://doi.org/10.1145/3287054

[52] Gierad Laput, Yang Zhang, and Chris Harrison. 2017. Synthetic Sensors: Towards General-Purpose Sensing. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 3986–3999. https://doi.org/10.1145/3025453.3025773

[53] Josephine Lau, Benjamin Zimmerman, and Florian Schaub. 2018. Alexa, are you listening? Privacy perceptions, concerns and privacy-seeking behaviors with smart speakers. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (2018), 1–31.

[54] Josephine Lau, Benjamin Zimmerman, and Florian Schaub. 2018. Alexa, Are You Listening?: Privacy Perceptions, Concerns and Privacy-seeking Behaviors with Smart Speakers. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW (Nov. 2018), 1–31. https://doi.org/10.1145/3274371

[55] Adam J. Lee, Jacob T. Biehl, and Conor Curry. 2018. Sensing or Watching?: Balancing Utility and Privacy in Sensing Systems via Collection and Enforcement Mechanisms. In *Proceedings of the 23nd ACM on Symposium on Access Control Models and Technologies*. ACM, Indianapolis Indiana USA, 105–116. https://doi.org/10.1145/3205977.3205983

[56] Min Kyung Lee, Karen P. Tang, Jodi Forlizzi, and Sara Kiesler. 2011. Understanding Users' Perception of Privacy in Human-Robot Interaction. In *Proceedings of the 6th International Conference on Human-Robot Interaction* (Lausanne, Switzerland) *(HRI '11)*. Association for Computing Machinery, New York, NY, USA, 181–182. https://doi.org/10.1145/1957656.1957721

[57] Christopher Lima, Diogo Gomes, and Rui Aguiar. 2012. Pervasive CSCW for smart spaces communities. In *2012 IEEE International Conference on Pervasive Computing and Communications Workshops*. 118–123. https://doi.org/10.1109/PerComW.2012.6197462

[58] Jiacheng Lin, Yang Li, and Guanci Yang. 2021. FPGAN: Face de-identification method with generative adversarial networks for social robots. *Neural Netw.* 133 (Jan. 2021), 132–147.

[59] Beth Logan, Jennifer Healey, Matthai Philipose, Emmanuel Munguia Tapia, and Stephen Intille. 2007. A Long-Term Evaluation of Sensing Modalities for Activity Recognition. In *Proceedings of the 9th International Conference on Ubiquitous Computing* (Innsbruck, Austria) *(UbiComp '07)*. Springer-Verlag, Berlin, Heidelberg, 483–500.

[60] Ching-Hu Lu and Li-Chen Fu. 2009. Robust Location-Aware Activity Recognition Using Wireless Sensor Network in an Attentive Home. *IEEE Transactions on Automation Science and Engineering* 6, 4 (2009), 598–609. https://doi.org/10.1109/TASE.2009.2021981

[61] Christoph Lutz and Aurelia Tamò. 2015. RoboCode-Ethicists: Privacy-Friendly Robots, an Ethical Responsibility of Engineers?. In *Proceedings of the ACM Web Science Conference* (Oxford, United Kingdom) *(WebSci '15)*. Association for Computing Machinery, New York, NY, USA, Article 21, 12 pages. https://doi.org/10.1145/2786451.2786465

[62] Christoph Lutz and Aurelia Tamó-Larrieux. 2020. The robot privacy paradox: Understanding how privacy concerns shape intentions to use social robots. *Human-Machine Communication* 1 (2020), 87–111.

[63] Dimitrios Lymberopoulos, Athanasios Bamis, and Andreas Savvides. 2008. Extracting Spatiotemporal Human Activity Patterns in Assisted Living Using a Home Sensor Network. In *Proceedings of the 1st International Conference on PErvasive Technologies Related to Assistive Environments* (Athens, Greece) *(PETRA '08)*. Association for Computing Machinery, New York, NY, USA, Article 29, 8 pages. https://doi.org/10.1145/1389586.1389621

[64] G M Lyons, K M Culhane, D Hilton, P A Grace, and D Lyons. 2005. A description of an accelerometer-based mobility monitoring technique. *Med. Eng. Phys.* 27, 6 (July 2005), 497–504.

[65] Karola Marky, Sarah Prange, Florian Krell, Max Mühlhäuser, and Florian Alt. 2020. “You just can’t know about everything”: Privacy Perceptions of Smart Home Visitors. In *19th International Conference on Mobile and Ubiquitous Multimedia*. ACM, Essen Germany, 83–95. https://doi.org/10.1145/3428361.3428464

[66] Karola Marky, Alexandra Voit, Alina Stöver, Kai Kunze, Svenja Schröder, and Max Mühlhäuser. 2020. ”I don’t know how to protect myself”: Understanding Privacy Perceptions Resulting from the Presence of Bystanders in Smart Environments. In *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*. ACM, Tallinn Estonia, 1–11. https://doi.org/10.1145/3419249.3420164

[67] Pardis Emami Naeini, Sruti Bhagavatula, Hana Habib, Martin Degeling, Lujo Bauer, Lorrie Faith Cranor, and Norman Sadeh. 2017. Privacy Expectations and Preferences in an IoT World. In *Thirteenth Symposium on Usable Privacy and Security (SOUPS 2017)*. USENIX Association, Santa Clara, CA, 399–412. https://www.usenix.org/conference/soups2017/technical-sessions/presentation/naeini

[68] Marketta Niemelä and Helinä Melkas. 2019. *Robots as Social and Physical Assistants in Elderly Care*. Springer Singapore, Singapore, 177–197. https://doi.org/10.1007/978-981-13-7725-9_10

[69] Marketta Niemelä, Lina van Aerschot, Antti Tammela, and Iina Aaltonen. 2017. A Telepresence Robot in Residential Care: Family Increasingly Present, Personnel Worried About Privacy. In *Social Robotics*, Abderrahmane Kheddar, Eiichi Yoshida, Shuzhi Sam Ge, Kenji Suzuki, John-John Cabibihan, Friederike Eyssel, and Hongsheng He (Eds.). Springer International Publishing, Cham, 85–94.

[70] Marketta Niemelä, Lina Van Aerschot, Antti Tammela, Iina Aaltonen, and Hanna Lammi. 2021. Towards Ethical Guidelines of Using Telepresence Robots in Residential Care. *International Journal of Social Robotics* 13 (06 2021). https://doi.org/10.1007/s12369-019-00529-8

[71] P. Onorato, Tommaso Rosi, Eugenio Tufino, Caterina Caprara, and Massimiliano Malgieri. 2021. Quantitative experiments in a distance lab: studying blackbody radiation with a smartphone. *European Journal of Physics* 42 (07 2021), 045103. https://doi.org/10.1088/1361-6404/abfd3e

[72] Leif Oppermann, Alexander Boden, Britta Hofmann, Wolfgang Prinz, and Stefan Decker. 2019. Beyond HCI and CSCW: Challenges and Useful Practices Towards a Human-Centred Vision of AI and IA. In *Proceedings of the Halfway to the Future Symposium 2019* (Nottingham, United Kingdom) *(HTTF 2019)*. Association for Computing Machinery, New York, NY, USA, Article 37, 5 pages. https://doi.org/10.1145/3363384.3363481

[73] Leysia Palen and Paul Dourish. 2003. Unpacking "Privacy" for a Networked World. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Ft. Lauderdale, Florida, USA) *(CHI ’03)*. Association for Computing Machinery, New York, NY, USA, 129–136. https://doi.org/10.1145/642611.642635

[74] Martin Pielot, Rodrigo de Oliveira, Haewoon Kwak, and Nuria Oliver. 2014. Didn’t You See My Message? Predicting Attentiveness to Mobile Instant Messages. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI ’14)*. Association for Computing Machinery, New York, NY, USA, 3319–3328. https://doi.org/10.1145/2556288.2556973

[75] Dave Randall. 2003. *Living Inside a Smart Home: A Case Study*. Springer London, London, 227–246. https://doi.org/10.1007/1-85233-854-7_12

[76] Nisarg Raval, Animesh Srivastava, Kiron Lebeck, Landon Cox, and Ashwin Machanavajjhala. 2014. MarkIt: Privacy Markers for Protecting Visual Secrets. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication* (Seattle, Washington) *(UbiComp ’14 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 1289–1295. https://doi.org/10.1145/2638728.2641707

[77] Blaine Reeder, Jane Chung, Kate Lyden, Joshua Winters, and Catherine M Jankowski. 2020. Older women’s perceptions of wearable and smart home activity sensors. *Inform. Health Soc. Care* 45, 1 (Jan. 2020), 96–109.

[78] Delphine Reinhardt, Monisha Khurana, and Luca Hernández Acosta. 2021. “I still need my privacy”: Exploring the level of comfort and privacy preferences of German-speaking older adults in the case of mobile assistant robots. *Pervasive and Mobile Computing* 74 (2021), 101397.

[79] Delphine Reinhardt, Monisha Khurana, and Luca Hernández Acosta. 2021. “I still need my privacy”: Exploring the level of comfort and privacy preferences of German-speaking older adults in the case of mobile assistant robots. *Pervasive and Mobile Computing* 74 (2021), 101397. https://doi.org/10.1016/j.pmcj.2021.101397

[80] P. Riehmann, M. Hanfler, and B. Froehlich. 2005. Interactive Sankey diagrams. In *IEEE Symposium on Information Visualization, 2005. INFOVIS 2005*. 233–240. https://doi.org/10.1109/INFVIS.2005.1532152

[81] Matthew Rueben, Frank J. Bernieri, Cindy M. Grimm, and William D. Smart. 2016. User feedback on physical marker interfaces for protecting visual privacy from mobile robots. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 507–508. https://doi.org/10.1109/HRI.2016.7451829

[82] Matthew Rueben, Frank J. Bernieri, Cindy M. Grimm, and William D. Smart. 2017. Framing Effects on Privacy Concerns about a Home Telepresence Robot. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (Vienna, Austria) *(HRI ’17)*. Association for Computing Machinery, New York, NY, USA, 435–444. https://doi.org/10.1145/2909824.3020218

[83] Matthew Rueben, William D. Smart, Cindy M. Grimm, and Maya Cakmak. 2017. Privacy-Sensitive Robotics. In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*. ACM, Vienna Austria, 425–426. https://doi.org/10.1145/3029798.3029805

[84] Mukesh Saini, Pradeep K. Atrey, Sharad Mehrotra, and Mohan Kankanhalli. 2014. W3-Privacy: Understanding What, When, and Where Inference Channels in Multi-Camera Surveillance Video. *Multimedia Tools Appl.* 68, 1 (jan 2014), 135–158. https://doi.org/10.1007/s11042-012-1207-9

[85] Jeremy Schiff, Marci Meingast, Deirdre K. Mulligan, Shankar Sastry, and Ken Goldberg. 2009. *Respectful Cameras: Detecting Visual Markers in Real-Time to Address Privacy Concerns.* Springer London, London, 65–89. https://doi.org/10.1007/978-1-84882-301-3_5

[86] Trenton Schulz and Jo Herstad. 2017. Walking Away from the Robot: Negotiating Privacy with a Robot. In *Proceedings of the 31st British Computer Society Human Computer Interaction Conference* (Sunderland, UK) *(HCI '17)*. BCS Learning; Development Ltd., Swindon, GBR, Article 83, 6 pages. https://doi.org/10.14236/ewic/HCI2017.83

[87] Trenton Schulz, Jo Herstad, and Harald Holone. 2018. Privacy at Home: An Inquiry into Sensors and Robots for the Stay at Home Elderly. In *Human Aspects of IT for the Aged Population. Applications in Health, Assistance, and Entertainment: 4th International Conference, ITAP 2018, Held as Part of HCI International 2018, Las Vegas, NV, USA, July 15–20, 2018, Proceedings, Part II* (Las Vegas, NV, USA). Springer-Verlag, Berlin, Heidelberg, 377–394. https://doi.org/10.1007/978-3-319-92037-5_28

[88] Stephan Schwan and Roland Riempp. 2004. The cognitive benefits of interactive videos: Learning to tie nautical knots. *Learning and instruction* 14, 3 (2004), 293–305.

[89] Elaine Sedenberg, John Chuang, and Deirdre Mulligan. 2016. Designing Commercial Therapeutic Robots for Privacy Preserving Systems and Ethical Research Practices Within the Home. *International Journal of Social Robotics* 8 (06 2016). https://doi.org/10.1007/s12369-016-0362-y

[90] Adriana M Seelye, Katherine V Wild, Nicole Larimer, Shoshana Maxwell, Peter Kearns, and Jeffrey A Kaye. 2012. Reactions to a remote-controlled video-communication robot in seniors' homes: a pilot study of feasibility and acceptance. *Telemed. J. E. Health.* 18, 10 (Dec. 2012), 755–759.

[91] Maxwell Szymanski, Martijn Millecamp, and Katrien Verbert. 2021. Visual, Textual or Hybrid: The Effect of User Expertise on Different Explanations. In *26th International Conference on Intelligent User Interfaces* (College Station, TX, USA) *(IUI '21)*. Association for Computing Machinery, New York, NY, USA, 109–119. https://doi.org/10.1145/3397481.3450662

[92] Madiha Tabassum, Jess Kropczynski, Pamela Wisniewski, and Heather Richter Lipford. 2020. Smart Home Beyond the Home: A Case for Community-Based Access Control. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. ACM, Honolulu HI USA, 1–12. https://doi.org/10.1145/3313831.3376255

[93] Robert Templeman, Mohammed Korayem, David Crandall, and Apu Kapadia. 2014. PlaceAvoider: Steering First-Person Cameras away from Sensitive Spaces. https://doi.org/10.14722/ndss.2014.23014

[94] Peter Tolmie, Andy Crabtree, Tom Rodden, James Colley, and Ewa Luger. 2016. "This Has to Be the Cats": Personal Data Legibility in Networked Sensing Systems. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work; Social Computing* (San Francisco, California, USA) *(CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 491–502. https://doi.org/10.1145/2818048.2819992

[95] Meg Tonkin, Jonathan Vitale, Suman Ojha, Jesse Clark, Sammy Pfeiffer, William Judge, Xun Wang, and Mary-Anne Williams. 2017. Embodiment, Privacy and Social Robots: May I Remember You?. In *Social Robotics*, Abderrahmane Kheddar, Eiichi Yoshida, Shuzhi Sam Ge, Kenji Suzuki, John-John Cabibihan, Friederike Eyssel, and Hongsheng He (Eds.). Springer International Publishing, Cham, 506–515.

[96] Sarah Turner, Jason R.C. Nurse, and Shujun Li. 2022. "It Was Hard to Find the Words": Using an Autoethnographic Diary Study to Understand the Difficulties of Smart Home Cyber Security Practices. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI EA '22)*. Association for Computing Machinery, New York, NY, USA, Article 34, 8 pages. https://doi.org/10.1145/3491101.3503577

[97] Alan R. Wagner. 2018. An Autonomous Architecture That Protects the Right to Privacy. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society* (New Orleans, LA, USA) *(AIES '18)*. Association for Computing Machinery, New York, NY, USA, 330–334. https://doi.org/10.1145/3278721.3278768

[98] Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T. Campbell. 2014. StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Seattle, Washington) *(UbiComp '14)*. Association for Computing Machinery, New York, NY, USA, 3–14. https://doi.org/10.1145/2632048.2632054

[99] Jing Wei, Benjamin Tag, Johanne R Trippas, Tilman Dingler, and Vassilis Kostakos. 2022. What Could Possibly Go Wrong When Interacting with Proactive Smart Speakers? A Case Study Using an ESM Application. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for

Computing Machinery, New York, NY, USA, Article 276, 15 pages. https://doi.org/10.1145/3491102.3517432

[100] Peter Worthy, Ben Matthews, and Stephen Viller. 2016. Trust Me: Doubts and Concerns Living with the Internet of Things. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (Brisbane, QLD, Australia) *(DIS '16)*. Association for Computing Machinery, New York, NY, USA, 427–434. https://doi.org/10.1145/2901790.2901890

[101] Ya-Huei Wu, Jérémy Wrobel, Mélanie Cornuet, Hélène Kerhervé, Souad Damnée, and Anne-Sophie Rigaud. 2014. Acceptance of an assistive robot in older adults: a mixed-method study of human-robot interaction over a 1-month period in the Living Lab setting. *Clin. Interv. Aging* 9 (May 2014), 801–811.

[102] Guanci Yang, Jing Yang, Weihua Sheng, Francisco Erivaldo Fernandes Junior, and Shaobo Li. 2018. Convolutional Neural Network-Based Embarrassing Situation Detection under Camera for Social Robot in Smart Homes. *Sensors* 18, 5 (2018). https://doi.org/10.3390/s18051530

[103] Rayoung Yang and Mark W. Newman. 2013. Learning from a Learning Thermostat: Lessons for Intelligent Systems for the Home. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Zurich, Switzerland) *(UbiComp '13)*. Association for Computing Machinery, New York, NY, USA, 93–102. https://doi.org/10.1145/2493432.2493489

[104] Yaxing Yao, Justin Reed Basdeo, Smirity Kaushik, and Yang Wang. 2019. Defending My Castle: A Co-Design Study of Privacy Mechanisms for Smart Homes. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, Glasgow Scotland Uk, 1–12. https://doi.org/10.1145/3290605.3300428

[105] Yaxing Yao, Justin Reed Basdeo, Oriana Rosata Mcdonough, and Yang Wang. 2019. Privacy perceptions and designs of bystanders in smart homes. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–24.

[106] Eric Zeng, Shrirang Mare, and Franziska Roesner. 2017. End User Security and Privacy Concerns with Smart Homes. In *Proceedings of the Thirteenth USENIX Conference on Usable Privacy and Security* (Santa Clara, CA, USA) *(SOUPS '17)*. USENIX Association, USA, 65–80.

[107] Chenyang Zhang, Yingli Tian, and Elizabeth Capezuti. 2012. Privacy Preserving Automatic Fall Detection for Elderly Using RGBD Cameras. In *Proceedings of the 13th International Conference on Computers Helping People with Special Needs - Volume Part I* (Linz, Austria) *(ICCHP'12)*. Springer-Verlag, Berlin, Heidelberg, 625–633. https://doi.org/10.1007/978-3-642-31522-0_95

[108] Qiang Alex Zhao and John T. Stasko. 1998. Evaluating Image Filtering Based Techniques in Media Space Applications. In *Proceedings of the 1998 ACM Conference on Computer Supported Cooperative Work* (Seattle, Washington, USA) *(CSCW '98)*. Association for Computing Machinery, New York, NY, USA, 11–18. https://doi.org/10.1145/289444.289450

[109] Serena Zheng, Noah Apthorpe, Marshini Chetty, and Nick Feamster. 2018. User Perceptions of Smart Home IoT Privacy. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 200 (nov 2018), 20 pages. https://doi.org/10.1145/3274469

[110] Martina Ziefle, Simon Himmel, and Wiktoria Wilkowska. 2011. When Your Living Space Knows What You Do: Acceptance of Medical Home Monitoring by Different Technologies. In *Information Quality in e-Health*, Andreas Holzinger and Klaus-Martin Simonic (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 607–624.

A APPENDIX

A.1 Study Questionnaire

The following questionnaire was presented to the participants for each sensor in the study after every exposure. The questionnaire and scenarios have been adapted from [67].
The scenario presented was of the format [location] + [sensor_name] + [function] + [example_usage]. An example is presented below.

For each scenario presented in this questionnaire, assume that the sensor is present in your home, data is collected by the manufacturer, and retained for a long term (more than 6 months).

Scenario 1: The living room has a thermal camera pointing towards the kitchen that captures a thermal image used for detecting temperature variations (e.g., when you start cooking).

Q1. This use of my data would be beneficial to me. (5-point, Strongly Disagree to Strongly Agree)
Q2. I think scenarios like this happen today. (5-point, Strongly Disagree to Strongly Agree)
Q3. (If "disagree" or "strongly disagree" for Q2) I think scenarios like this will happen within 2 years. (5-point, Strongly Disagree to Strongly Agree)

Q4. (If "disagree" or "strongly disagree" for Q3) I think scenarios like this will happen within 10 years. (5-point, Strongly Disagree to Strongly Agree)
Q5a. How would you feel about the data collection in the situation described above if you were not told with whom the data would be shared, how long it would be kept, or how long it would be used for? (5-point, Very Uncomfortable to Very Comfortable)
Q5b. How would you feel about the data collection in the situation described above if you were given no additional information about the scenario? (5-point, Very Uncomfortable to Very Comfortable)
Q6a. I would like to be notified every time this data collection occurs. (5-point, Strongly Disagree to Strongly Agree)
Q6b. I would like to be notified only the first time this data collection occurs. (5-point, Strongly Disagree to Strongly Agree)
Q6c. I would like to be notified every once in a while when this data collection occurs. (5-point, Strongly Disagree to Strongly Agree)
Q7. If you had the choice, would you allow or deny this data collection?

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