Reshaping the Smart Home Research and Development in the Pandemic Era: Considerations around Scalable and Easy-to-Install Design

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Smart home research has traditionally included visiting participants' homes to build testbed environments and evaluate their experience. However, in-person home deployment poses limitations around scalability and is not a feasible method in the context of the COVID-19 pandemic. The smart home research community is now facing the need to reshape and innovate research methods and design approaches. This study introduces a scalable smart home platform prototype that demonstrates possible solutions to address issues and limitations posed by the pandemic, such as improving package design, enabling user-driven installation, and facilitating remote evaluation and maintenance. The prototype uses off-the-shelf products with specially designed packaging to ensure interoperability as well as ease of shipping and installation. In this study, the prototype kits were shipped to participants' homes to understand and evaluate user perceptions and experiences around installation and initial use. Responses to a post-installation questionnaire and remote monitoring of system status showed that the participants easily completed their self-installation of the prototype without any on-site support. The study also showed potential for a scenario-based evaluation of the prototype using a remote, contactless research procedure.

CCS Concepts: • **Human-centered computing → Field studies**; **Usability testing**; **Empirical studies in HCI**; **Ubiquitous and mobile computing design and evaluation methods**.

Additional Key Words and Phrases: smart home; research method design; scalability; user experience; case study; pandemic

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1 INTRODUCTION

For the last couple of decades, data-driven smart home research has been conducted from diverse perspectives. Localization methods have used various in-home sensors to predict and track multiple inhabitants' locations [4, 22, 53]. Machine learning techniques have enabled human activity recognition and anomaly detection [4, 8, 49, 50]. Smart home architectures with capabilities to learn user preferences have contributed to automated and personalized smart home services [11, 21, 47]. The importance of such smart home research has become more apparent during the current COVID-19 pandemic as people are spending more time than ever in their homes. The adoption of new routines and lifestyles is intensifying people's needs around remote connections, caregiving, convenience, security, and comfort, leading to an expectation that the smart home market will reach USD 317 billion by 2026, up 5% from pre-COVID-19 forecasts [1].

Despite technological achievements and market growth, smart home research has been tested in restricted settings, limiting the possibility of generalizing the findings to real-world applications. Such restricted evaluation is attributed to non-scalable and expensive research methods. The typical research procedure includes testbed construction for data collection and technical service provision, which requires high costs, longer time, and numerous on-site tasks. Typically, a research team visits a participant's home to configure the network, install sensors, and turn home appliances to smart objects by attaching computing gadgets. Remote tasks, such as device status monitoring, device maintenance, and data refinement, also entail severe operation costs. There have been attempts to tackle the scalability issue by presenting an easy-to-install smart home kit [13, 23] or crowdsourcing-based smart home data collection techniques [16, 24]. However, these works required a high degree of technical knowledge from participants, which is likely to lead to high user failure and limited acceptance. Optimization for a subset of the user population characterized by advanced technical skills could also result in exclusion of key user profiles that could especially benefit from the use of smart home technologies, such as older adults, people with mobility limitations, and people with low technology experience. Furthermore, existing research systems have limited applicability to support various smart home use cases due to limited interoperability with third party devices/services. In addition to these limitations, the COVID-19 pandemic poses additional challenges to conducting smart home research as in-person visits are prohibited or discouraged to ensure public safety. To this end, it is necessary to reshape the overall smart home research pipeline in a scalable and safe manner.

This case study presents a smart home platform prototype and related research procedure to reshape the smart home research pipeline in a scalable and safe manner. This case study first describes the platform architecture composed of essential research building blocks and a low-cost implementation that participants can easily and safely install. We also present remote and secure operations of the proposed research building blocks as well as user instruction and the delivery process. An evaluation of the installation process and initial use demonstrated that the prototype design supported the simplicity of the self-installation. This case study also discusses the participants' feedback and its implications on advancing future practices in the smart home research community.

2 RELATED WORKS

2.1 Traditional Smart Home Research

A traditional smart home research pipeline has included in-home visits for testbed construction. Typical smart home testbeds include (1) sensor devices to collect in-home environment and user behavior data (e.g., temperature/humidity, electricity use, movement detection), (2) actuator devices to provide remote or automated service actions (e.g., smart TV, smart air conditioner, smart thermostat), and (3) a home gateway or server device that collects in-home sensor data, triggers an actuator's function, and transmits home data to a data server outside for analysis or research purpose. Since such home network configuration requires expert knowledge, it is usually required that a technician (or technicians) visit participants' homes for installation and setup, or for research participants to be taken into a lab setting. For example, Dawadi et al. [15] invited participants to an on-campus smart home testbed to evaluate an automated smart home system for assessing participants' cognitive health. In this on-campus smart home testbed, tens of sensors including infrared motion detectors, door sensors, other environment sensors were installed to keep track of participants' behaviors in detail. Kim et al. [26] deployed multiple smart home testbeds including multiple smart plugs as energy usage sensors and a raspberry pi board as a sensor gateway.

However, such a traditional method has scalability and sustainability issues. Smart home testbed construction requiring a technician's in-home visit is costly, making it infeasible to construct multiple testbeds and to recruit participants across a large geographic area. Especially, when an in-home visit is not allowed due to a catastrophic situation, such as the COVID-19 pandemic, building a testbed becomes impossible using this method. Inviting participants to a lab setting provides only a controlled and small set of experiment data, which is not appropriate for longitudinal and realistic smart home studies.

2.2 Kit-based Approach to Smart Home Research

Hu et al. [23] tackled the aforementioned scalability issue of the traditional testbed-based smart home research method. To overcome the limitation and facilitate a large scale smart home research, they presented an easy-to-install lightweight smart home testbed kit, called *Smart Home in a Box (SHiB)*, that is easily self-installed and does not require any customization or training to smart home users. This kit includes a server box (i.e., home gateway), an Ethernet cable for the server box, binary motion sensors, temperature/magnetic door sensors, and sensor relay modules. These modules were put together into a box and delivered to a participant's home with an instruction document. Upon its arrival, the participants were instructed to power up and connect the server box to the Internet, locate sensor relay modules, attach binary motion sensors to the ceiling, and install temperature and magnetic door sensors. The installation locations of delivered sensors were described in the instruction document. They recruited older adults as participants to evaluate its usability and gather practical feedback.

Even though all required setups were preconfigured before the kit's delivery, only a quarter of the entire participants successfully installed the delivered hardware modules. Such a high failure rate was attributed to many different reasons. Most participants failed to install a device if it was hard to understand what the device was used for or its installation requires understanding the operation mechanism. For example, participants considered the server box confusing, intimidating, and fragile, because they did not understand what it is for, and waited for a technician instead of trying it by themselves. Many participants also failed to install the relay modules because they do not understand how it works. In addition, it could be dangerous to ask people with physical limitations to attach multiple motion sensors to the ceiling. Overall, the abstraction of technical details were not enough, and the usability of the smart home kit was not carefully designed. It could also raise a privacy issue because too many sensors were deployed, making it possible to associate sensor readings to specific user activities.

2.3 Crowdsourcing-based Smart Home Data Collection

Crowdsourcing the collection of smart home data using open-source data collection software connected to devices that users already own [16, 24] is an alternative method to facilitate smart home research. Huang et al. [24] point out that traditional smart home research methods have scaling and labeling challenges. Deploying physical devices on the participants' home networks often require significant effort, and a large corpus of ground-truth labels of devices and collected data is mostly absent or not publicly available. They present *IoT Inspector* to overcome these limitations by allowing users to download a desktop application that leverages *ARP scanning and spoofing* to intercept home network traffics between the network router and connected devices to it. The intercepted packets are integrated with device identities that are automatically annotated using service discovery protocols or manually labeled by the users. The integrated information is preprocessed and transmitted to the database server by IoT Inspector. From the collected data, IoT inspector helps users enhance their awareness of security and privacy concerns by presenting relevant information such as unencrypted traffics or network endpoints' identities. HomeNet Profiler [16] employs similar techniques to measure home network configuration and performance.

Such crowdsourcing methods are effective to scale out smart home data collection. However, they have interoperability and usability issues when expanding into general purpose smart home research. For example, many off-the-shelf home devices, including sensors and actuators, encrypt their packets and allow an access to their data or functions through APIs requiring token-based authentication. Without complying with those protocol stacks, collected data by IoT Inspector cannot be used for popular smart home research topics including activity recognition and fall detection. This approach also raises a serious usability issue when applied to a diverse user base, including users of various ages, abilities and technology experience, although potential benefits of using smart home technologies may be greater for older adults and people with physical and cognitive limitations. For example, its users need to understand a set of technical terms, such as MAC address, encryption, network endpoint, and data labeling, to complete all required steps while avoiding transmissions of any sensitive data. Such technologies or technical terms can easily confuse and intimidate non-tech-savvy users [23], leading to a failure of required research activities. Besides, such method is limited to home data collection and not capable of providing smart home services.

2.4 Use of Radio Frequency (RF) Signals in Smart Home Research

Radio frequency (RF) signal has been recently considered as a promising alternative of multi-modal sensors, such as temperature/humidity, motion, camera, for in-home user behavior analysis [22, 49, 56]. Hsu et al. [22] presented *Marko*, a system that identifies in-home users, builds each user's trajectory, and recognizes the user's behavior using raw RF signals. *Marko* is a wireless sensor that transmits an RF signal and processes its reflections from users and static objects. It uses a Convolutional Neural Network (CNN) to identify a user using the processed RF signal. RF signal can also be used for fall detection, which is a promising smart home application for care givers and recipients. Tian et al. [49] presented *Aryokee* that uses FMCW radio and a CNN model to characterize RF reflections and detect falling events. RF signal has been also used to recognize emotions of smart home users [56]. Zhao et al. [56] presented EQ-Radio that recognizes an in-home user's emotion by extracting the individual hearbeats from the wireless signal reflected off a person's body.

RF-based smart home technologies are promising because of its minimally invasive but generic nature. Hence, it can complement or replace some of the sensor technologies. However, it has a limited capability of capturing in-home user behavior or device usage patterns. For example, it cannot completely replace temperature/humidity data or electricity usage data because RF signals cannot deliver such domain-specific semantics. In addition, such a radio hardware is not widely used yet, and the radio signal could be easily distorted by other electronic devices in smart home environments. Therefore, RF-based technologies should be considered as an additional sensing method to the existing smart home technologies, not as a replacement.

3 DESIGN GOALS AND CONSIDERATIONS

The analysis and discussion of the existing works in Section 2 reveal that enabling the smart home research to be scalable, sustainable, and safe is not as easy as designing a new smart home architecture. To remove the needs for expert home visits in the cycle of smart home research, it is necessary to transfer the control across the entire research pipeline from researchers and/or technicians to users with a wide range of technological literacy. First, technical details and terminologies should be simplified, and the installation procedure should be made transparent for participants with the minimum level of technological literacy, such as older adults. Especially, any kinds of structural changes in a participant's home should not be required because such changes may require relevant expert knowledge and cause frustration of the participant [10]. Interoperability is also a critical requirement [44] to enable the inclusion of custom and off-the-shelf devices/services and to support a wide range of smart home use cases. Cost efficiency is another important requirement [10, 44], especially to conduct a large-scale smart home research or to facilitate the actual adoption of the smart home technologies in people's daily lives. Privacy preservation and data protection is also important as failure can lead to a catastrophic consequence when it is not carefully incorporated into the research process design [6, 19, 57]. This study aims to present not only a smart home platform and its prototype implementation but also the entire research procedure that is carefully designed so that researchers can offer features to and evaluate systems with participants of various characteristics, abilities and experiences, and conduct a large-scale smart home research without in-home visits and support.

4 SMART HOME PLATFORM PROTOTYPE

Defining necessary building blocks and choosing an appropriate framework is the most crucial part to a smart home research. This section presents this study's approaches to develop a smart home platform architecture and its prototype implementation. It is also described how the proposed method fulfills the design goals discussed in Section 3.

4.1 Smart Home Platform Architecture

Figure 1 shows the smart home platform architecture developed in this study, including the connections between its five main building blocks and data protection mechanisms. The *Internet-of-Things (IoT) device platform* connects *sensors and actuators* to *firmware and application development platform* to manipulate the data flow and control logic between the home environment and the smart home system. All recorded data from the IoT devices are sent to the *smart home data server* with timestamps. The *intelligence core* includes machine learning and data analysis modules to infer high-level information describing home situations and user behavior, and to decide on personalized service actions. The *integration platform* connects these three building blocks and third-party smart home products to complete a smart home platform to which additional devices or services can be deployed. Lastly, the *smart home front-end* interacts with the smart home data server and intelligence core to provide its user with information about their home that can be easily understood, while facilitating the remote system status monitoring and data analysis by the researchers. All data is encrypted before its transmission, and the cloud servers are protected using the industry standard security protocols.

4.2 Smart Home Use Case and Requirement Analysis

A key goal of the prototyping, in addition to the scalability requirements, is to build a versatile system that can support various use cases and be expanded for future research needs. However, a smart home architecture can be implemented in a variety of ways, and a single implementation

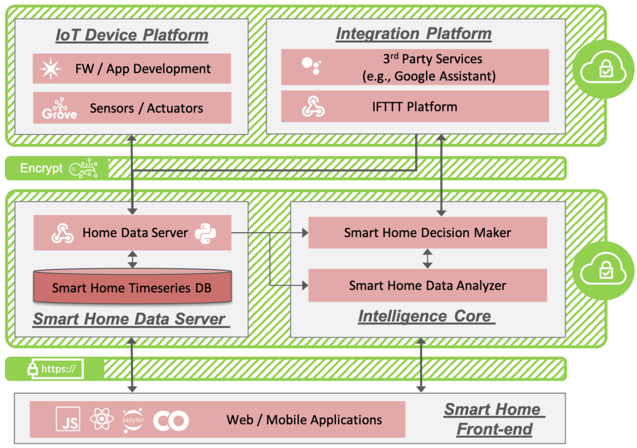


Fig. 1. The smart home platform development and implementation architecture

cannot support all smart home use cases. Therefore, it is critical to decide the most important target use cases of the prototype and make its implementation as expandable as possible. To achieve this goal, use cases and related user needs were first described with responses gathered from a set of user interviews, a large-scale online survey [34], and an exhaustive review of previous studies [7, 12, 19, 25, 31, 36, 37, 48, 59]. In addition, we interviewed eleven participants with various characteristics (Table 1) about their current in-home activities, pain points, and expectations for a future smart home. Ten key needs and concerns around safety, convenience, and self- and family care were identified from the interviews, and were compared with findings and use cases described in related literature. They were also reviewed by industry experts prior to selecting practical and feasible cases to focus on. The final set of use cases includes *safety and security*, *caregiving needs*, and *home energy and environment control*.

4.3 Smart Home Prototype Implementation

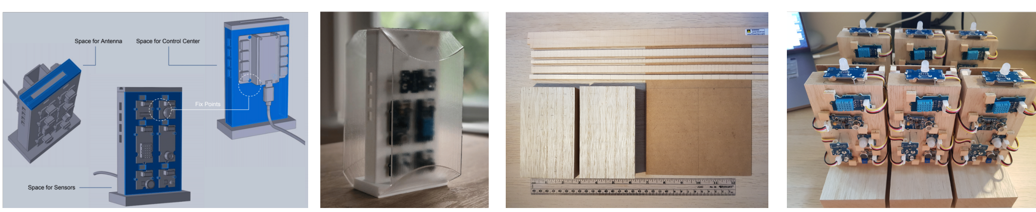
Selection of hardware components was done to optimize the system for remote and cloud-based maintenance and monitoring, with an aim to limit in-person contact and enable seamless distant operations. Also, the prototype employed an IoT development board with sensor modules that are currently widely available and used in order to ensure easier maintenance and to enhance accessibility. Table 2 shows the list of selected hardware and the total cost for developing the smart home prototype kit. The primary sensor readings can help smart home users develop an awareness of their preferred home environment and control it [12]. In addition, use of data analysis and machine

Table 1. Demographic information of interviewees for smart home use case analysis

Age		Income		Type or resident		Etc.		
18-29	2	0-50K	4	Apartment	4	Marital Status	Single	7
30-39	3	50-100K	3	Single family house	3		Married	4
40-49	1	100-200K	2	Dorm	1	Residential Env.	Urban	4
50-59	2	200K+	1	Condo	2		Suburban	6
60+	3	Unknown	1	Unknown	1		Unknown	1

Table 2. Costs for a small-scale production of the smart home platform prototype

Category	Module	Unit price	#	Total price
Sensor module	Particle Argon WiFi Dev. Board	\$27.92	1	\$27.92
	Grove Shield for Particle Mesh	\$2.90	1	\$2.90
	Grove Sensors (Motion, Brightness, UV Light, Sound, Air Quality, Temperature and Humidity)	\$32.95	1	\$32.95
	Grove Chainable RGB LED	\$5.99	1	\$5.99
Sensor module Frame	Wood Blocks	\$5.50	1	\$5.50
Power Strip	TP-Link HS300	\$64.99	1	\$64.99
Google Assistant	Nest Mini 2nd Gen. (for pilot study)	\$49.00	1	\$49.00
Android Tablet	Android Tablet 10" (for field study)	\$86.77	1	\$86.77
Total Price				\$189.25 (pilot) or \$227.02 (field)



(a) 3d-CAD for sensor kit (b) 3d-printed kit (c) Wood frame materials (d) Final sensor kits

Fig. 2. The overall production process of our smart home sensor kits

learning techniques on the collected sensor data can support the target use cases by enabling activity recognition and profiling [8, 28, 39, 40], emergent behavior detection [19, 36, 48, 54], and activity-aware energy saving [35, 41]. This choice also helps users preserve their privacy because none of their data can be directly associated with a specific user's identity and behavior due to the non-invasive nature of the selected modalities. In addition, the selected platforms (i.e., Particle, Nest, TP-Link, IFTTT) comply with the industry standard privacy and data protection protocols, including the cloud security and data encryption before its transmission. Besides, the cost is much lower than other off-the-shelf products or previous studies' prototypes while maintaining the capabilities of the data collection and manipulation. Slightly different combinations of hardware devices were used for two types of evaluation studies, pilot and field studies, and the details will be described in Section 5.

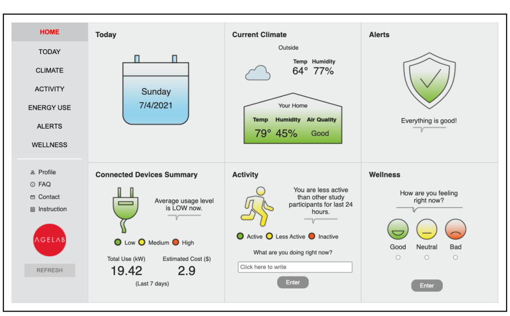
The sensor components were assembled into a solid kit for ease of shipping and installation. We tested two different methods to make the kit's base frame - 3d-printing (Figure 2a and 2b) and wood carpentry (Figure 2c and 2d) - and finally assembled the hardware modules with the wood frame for its lower cost and greater design flexibility over the 3d-printing one. The 3d-printing option can be better for manufacturing after the research phase.

The addition of the energy meter was done to support the identified use cases and needs regarding home energy and environment control. The prototype was designed to connect with various electronic devices and collect data about energy usage to illustrate possible ways of allowing users to control and be informed about home energy and environment. The selection of the internet-connected power strip was done to ensure seamless and secure cloud-based access to data, simple installation by end users, and easy access in the market. The primary data and statistics of energy usage could help the users develop an awareness of their behavior and determine how to change their device usage to save energy. The energy data can also be used to support the other use cases, such as security and caregiving needs, using the data patterns to recognize in-home user activity [20].

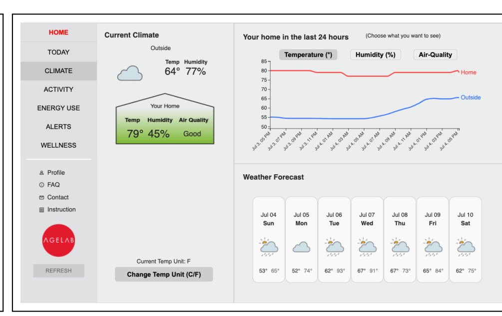
IFTTT[1] was used as the integration platform as it enables connections to a large variety of IoT products and services as an integrated logic. It also supports the webhook interface, which provides the flexibility to integrate custom features, such as the smart home data server, with the IFTTT platform and its registered services. For example, the prototype uses a Google Assistant device for labeling user activities such that IFTTT extracts text labels from the user input and forwards them to the data server using the webhook interface. Such a labeling method can be crucial for data-driven smart home research. Utilization of the IFTTT platform increases the prototype's interoperability, a critical requirement for a smart home platform and its acceptance [44], over past research approaches that have developed their own components from the scratch to maintain complete control over the entire research pipeline but sacrificed their system's interoperability with third-party services.

A home dashboard application was developed as the smart home front-end, enabling smart home users to understand in-home environments and their activities as well as to interact with

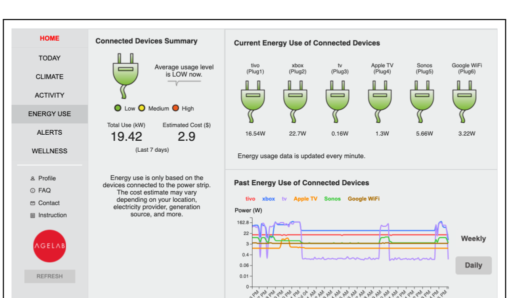
[1] https://ifttt.com/



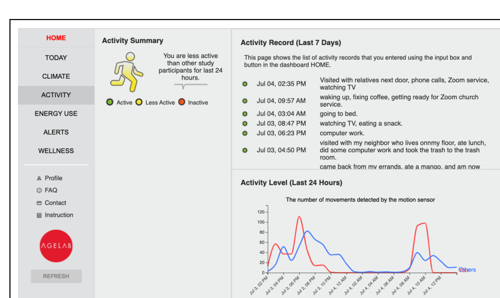
(a) Dashboard main page



(b) Dashboard climate page



(c) Dashboard energy use page



(d) Dashboard activity page

Fig. 3. Main pages of the home dashboard application

the deployed kits. Figure 3 shows sample pages of the home dashboard application. Basically, the dashboard application provides six different features: *Today*, *Climate*, *Activity*, *Energy Use*, *Alerts*, and *Wellness*. These six features were selected to support the three key use cases, *safety and security*, *caregiving needs*, and *home energy and environment control*, identified in the requirement analysis (see Section 4.2). In the dashboard application, the *Home* page shows the summary of the six features including text input user interfaces. The *Today* page shows today's date and the user's schedule using a calendar view. The *Climate* page shows the in-home and outside climate information and its 7-days forecast. The *Activity* page shows the user's activity records and patterns that have been entered by the user and observed by the motion sensor. The *Energy Use* page shows per-device energy use and its past records. The *Alerts* page provides a home monitoring feature that can be activated by users when they leave home. The *Wellness* page shows the perceived wellness records that have been manually entered by users. To support both mobile and web interfaces, *React*[2] framework was used for the application development, and *Ionic*[3] framework was used for the application conversion from web to mobile environment. Such a multi-modality support enhances the user experience by enabling users to access the application anywhere and anytime.

The smart home data server uses *TimescaleDB*[4], *Jupyter notebook*, and *Google Colab* to enable interactive data analysis and machine learning model development on the web environment. The trained models then are exported as back-end micro-services of the intelligence core. These building blocks were hosted on an AWS EC2 instance as RESTful services to facilitate HTTPS-based secure transactions using a public domain.

4.4 Self-Installation Procedure

In this study, the smart home prototype kits were delivered to the users' homes, and the users were asked to install them by themselves without on-site technical support. Figure 4 shows the overall installation steps that the users need to walk through. In short, this study includes two different phases, pilot and field study, and the installation procedure of the pilot study was refined

[2]https://reactjs.org/
[3]https://ionicframework.com/docs/react
[4]https://www.timescale.com/

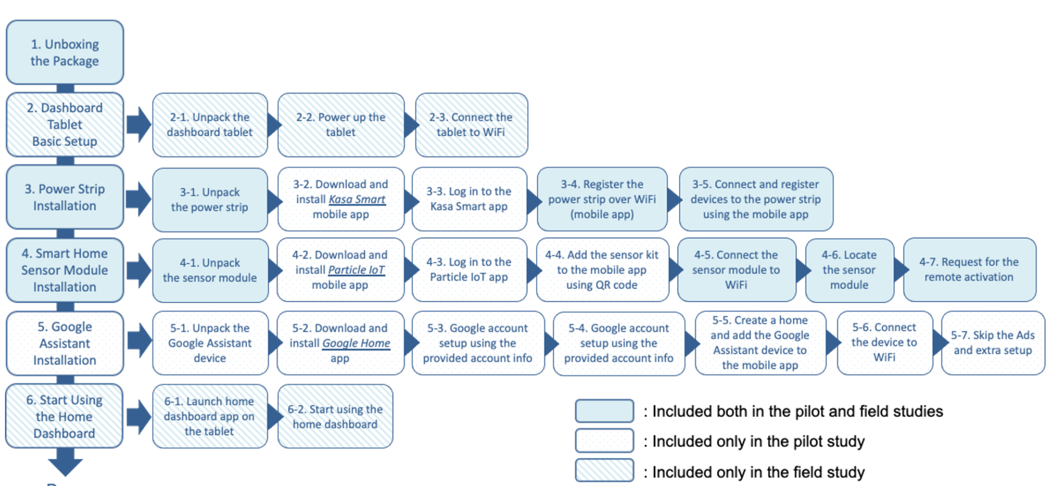
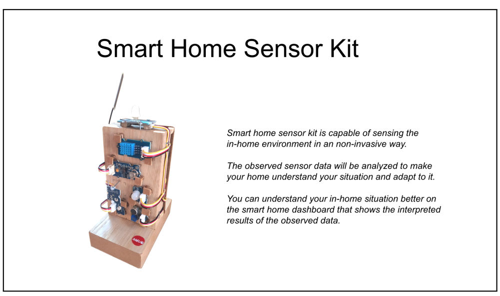


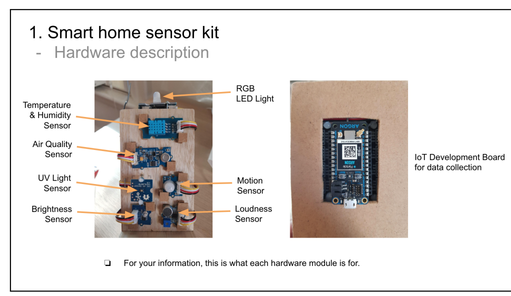
Fig. 4. The overall installation steps of the smart home prototype kits

in the field study based on its result and user feedback. The details will be described in Section 5. The installation procedure for each component basically consists of unpacking the components, downloading the mobile app, logging in to the mobile app, registering the device to the mobile app, connecting the device to WiFi, and placing the device at a preferred location. The power strip required one more step to connect devices to the power outlet and annotate the connected devices' names using the mobile app. The sensor kit also required an additional activation step, which was done by a remote researcher upon notification of the user.

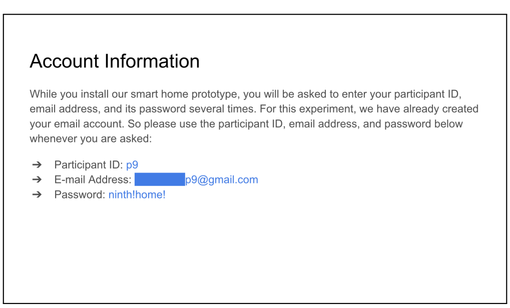
A user instruction document was created to ensure a successful self-installation by users. The document presented a step-by-step procedure to install the kit with plain language and helpful cues such as arrows and captions. Figure 5 illustrates sample pages from the instruction. To ensure that the instruction is easy to follow and understand, it was designed based on a walk-through of



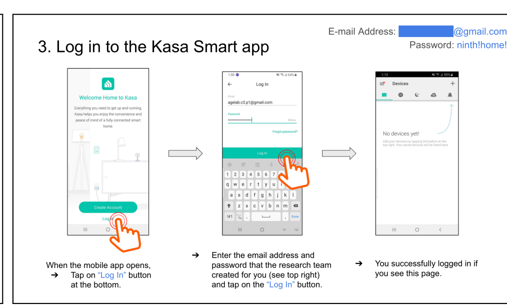
(a) Sensor kit description page



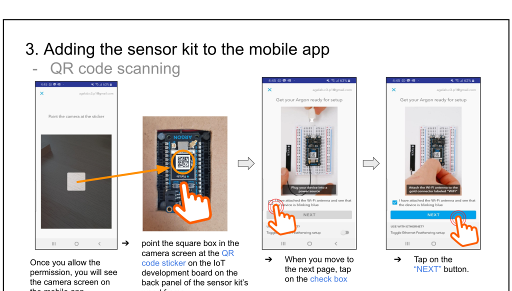
(b) Hardware module description page



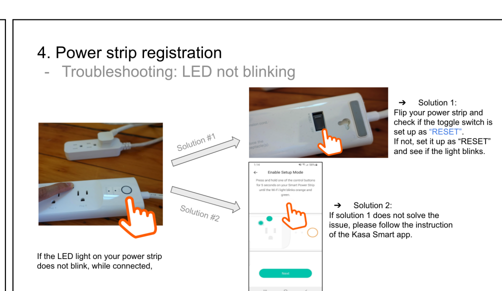
(c) Account information page



(d) Power strip login with account information



(e) Particle board registration page



(f) Power strip troubleshooting page

Fig. 5. Sample pages of user instruction for easy self-installation

how a user would follow the steps and which obstacles they would come across. The results from the user survey and interviews described earlier (Section 4.2) were also utilized. The participants' feedback from the pilot study was used to refine the instruction document of the field study.

More specifically, the document explains the purpose of each component and its attached hardware modules to make the users understand which benefits they can gain from using the kit (Figure 5a and Figure 5b). Delivering a user-friendly and detailed explanation is critical to prevent any failure due to the intimidating feelings or uncertainty as noted in the previous work [23]. For those with limited technology experience expressing frustration around managing different applications, including older adults with difficulty in switching across multiple screens and organizing applications during multitasking [58], the sign-on and setup process was designed so that each user could use one sign-on information across products and services connected to the prototype. For each user, an account was created in advance, and the account information was included in the instruction document. The account information was written on the first page of the document and at steps where log in was required (Figure 5c and Figure 5d). This process was also used to reduce potential privacy concerns as participants were not required to use their personal accounts. The document also included troubleshooting information for possible difficulties that may arise (Figure 5e and Figure 5f).

5 USER STUDY: EVALUATION OF THE INITIAL USER EXPERIENCE

Key drivers to user adoption of new technology include building confidence, empowering users, and user-friendliness, including ease of learning [33, 44]. As negative early experiences related to the design goals (see Section 3), such as installation difficulties, technology intimidation/anxiety, or poor privacy preservation, can deter a successful long-term acceptance, a careful evaluation of the initial user experience is crucial for scalable smart home research. In this work, pilot and field studies were conducted by sending the smart home prototypes to participants and asking them to install included components. After the self-installation, the participants answered a questionnaire about their self-installation experience and feedback.

The pilot study was conducted with a convenience sample of eight participants to identify risks in the self-installation and remote operation process design that can disturb the installation or harm the user experience before running an expensive and large scale field study across the country. The survey results and user feedback from the pilot study were used to enhance the field study design. For example, in the pilot study, primitive sensor/actuator devices were delivered to the participants' homes as of most existing smart home testbeds. To provide participants with meaningful information about each of designed features and enable participants to actively enter their inputs, in the field study, a home dashboard application installed in an Android tablet was added to the package. The Google Assistant device was removed in the field study because it did not have a critical use case in the early user experience evaluation. In addition, procedures of downloading and logging in to the mobile applications were removed in the field study. Instead, the research team completed them on the Android tablet before shipping the package and let the participants use the pre-configured tablet, not their personal mobile devices. Registration of the sensor module to the participant's account (step 4-4. in Figure 4 and step 3 in Figure 5e) was also completed before the shipment to reduce the participant's effort. The field study was split into two rounds due to the limited number of devices and for its stable operation.

5.1 Delivery of the Smart Home Prototype Kits

Both studies took a novel approach of packaging the smart home prototype kit in a deliverable form rather than employing the traditional researcher-driven approach, as illustrated in Figure 6. Upon completion of participant account setup, a sensor module, power strip, either the Google

(a) Packaging for shipping (b) A delivered package (c) Unboxing the package (d) Checking the package

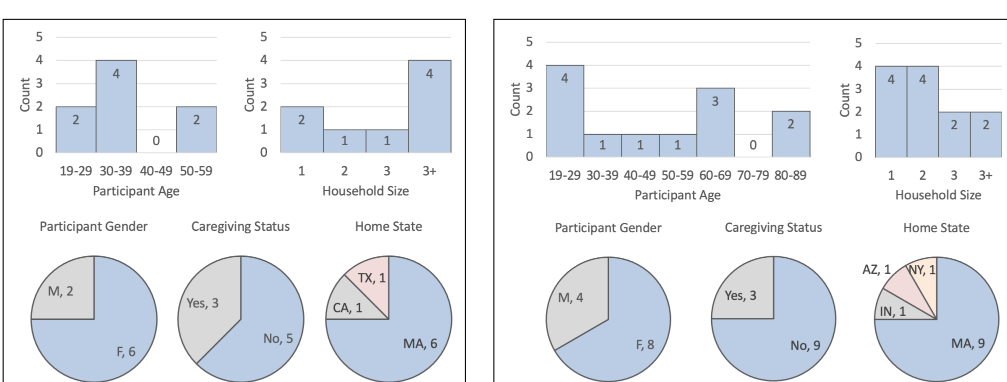
Fig. 6. The overall steps of the smart home prototype kit delivery

Assistant (pilot study) or the Android tablet (field study), and the instruction document were put together as a package and shipped to the participant's home. Then the participant received and unpacked the box to check for missing or damaged pieces. Once confirming that everything is fine, the participant began the self-installation process.

5.2 Participants

A convenience sample of eight participants were recruited from a university campus for the pilot study, while twelve participants were recruited from a laboratory-managed volunteer database that includes people across the United States. The demographic characteristics of the participants are shown in Figure 7. Overall, those with no computer science degree or prior experience with the employed devices were recruited to minimize possible bias. One of the participants uses a power chair due to a mobility impairment. The smart home kit packages have been sent to six different states, while 75% were sent to participants within Massachusetts. Such a geographical distribution helped the study evaluate if the proposed research pipeline and method are applicable to the participants living at a far distance, and to enable detection of possible design flaws when extended to a larger scale.

When recruiting participants for the field study, a set of screening questions were asked to understand participants' technology-related background, such as experience level, interest in technologies, technology adoption propensity, trust level in technologies, overall health, and current use of 29 different technologies. Figure 8 shows that, in general, the participants with



(a) Pilot Study (b) Field Study

Fig. 7. Demographic information of participants

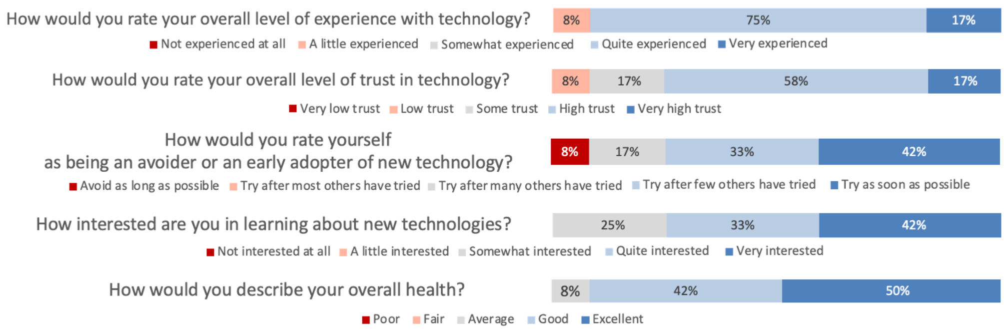


Fig. 8. Screening questions for field study participants' technology-related background

Which of the following technology products/services do you currently use, if any?

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
Smartphone	1	1	1	1	1	1	1	0	1	1	1	1
Tablet	0	1	1	0	0	0	1	1	0	1	1	1
Computer or laptop	1	1	1	1	1	1	1	1	1	1	1	1
Smart energy/utilities monitoring systems	0	0	0	0	0	1	1	1	0	0	1	1
Smart home appliance	0	0	0	1	0	0	0	0	0	0	0	0
Smart home security systems	0	0	0	0	0	1	0	0	0	0	0	0
Personal assistant or smart speaker	0	1	1	0	1	1	1	0	0	1	1	0
Smart fitness management system	0	0	1	0	0	1	0	0	0	1	1	0
Medication management platform or smart dispenser	0	0	0	0	0	0	0	0	0	0	0	0
Healthcare patient portals	1	1	0	1	1	1	1	1	1	1	1	1
Health or body metric tracker	0	1	0	0	0	0	0	0	1	1	1	0
Telemedicine platforms	0	0	0	0	0	0	0	0	1	0	0	0
Smart watch	0	0	1	0	0	1	0	0	0	1	1	0
Social media	0	1	1	1	1	1	1	1	1	1	0	1
Teleconferencing or video chat platform	0	1	0	1	1	1	1	1	1	1	1	1
Instant messaging client	0	1	1	1	1	1	1	1	0	1	0	1
Smart entertainment system	1	0	1	0	1	1	1	0	0	1	1	1
On-demand entertainment streaming service	1	1	1	1	1	1	1	0	1	1	1	1
Drone	0	0	0	0	1	0	0	0	0	0	0	0
Activity camera	0	0	0	0	0	0	0	0	0	0	0	0
3D printer	0	0	0	0	0	0	0	0	0	0	0	0
Cloud data storage	1	1	1	0	1	1	1	1	0	1	1	1
Mobile payment service	0	1	1	0	0	1	1	0	0	0	1	0
Ridesharing service	1	1	1	0	0	1	1	0	1	1	0	0
Internet-enabled grocery delivery service	0	1	1	0	1	0	1	0	0	1	0	1
Internet-enabled food ordering/delivery service	0	1	1	0	0	0	1	0	0	1	0	0
Internet-enabled housework service	0	0	0	0	0	0	0	0	0	0	0	0
Automated driving	0	0	1	0	0	0	0	0	0	0	0	0
Home or space sharing	0	1	1	0	0	1	0	0	1	0	0	0

Fig. 9. Field study participants' current use of technologies

a few exception considered themselves experienced and interested in technologies. In addition, participants were generally open to technology adoption with a high level of trust. Figure 9 shows that most participants were currently using common technologies, such personal mobile devices and popular internet-based services. The colored box annotated by '1' indicates *'currently using the technology'*, and '0' indicates *'currently not using the technology'*. On the other hand, many participants were not using smart home technologies (e.g., smart energy monitoring, smart home appliance, smart home security systems), healthcare solutions (e.g., smart fitness management, tele-medicine platform), and recent advanced technologies (e.g., drone, autonomous driving).

5.3 Questionnaire: Evaluation of the Installation Process

Table 3 shows the list of questions that were asked to the participants after the completion of their self-installation. Each row of the table shows either a common question asked in the pilot and field studies or a difference in the question between two studies. The questionnaire included items about the location and ease of self-installation for each module (questions 1-16), evaluation of the instruction document and the overall installation process (questions 17-21), perceived length of the installation process (question 22), perceived privacy concerns and usability (questions 23 and 24), general satisfaction of the prototype kit (questions 25 and 26), and any other comments (question 27). The list of questions were refined in the field study based on the lessons and changes from the pilot study. For example, questions about the Google Assistant device (question 7-9, 15) were removed, while those about the dashboard tablet (questions 10, 11, 16) were added. In addition, questions that could be answered in post-study interviews (questions 20, 21, 24) were removed in the field study questionnaire. Additional questions (questions 12, 19, 23.2 - 23.5, 26-27) were included in the field study to better understand the helpfulness of the instruction document, influential variables of the perceived privacy, and the usability of the prototype kit.

Table 3. Questions asked to gather initial feedback and to evaluate the self-installation process

No.	Pilot Study Questions	Field Study Questions
1	Where did you install or setup the power strip? (Please select multiple options if you use the room for other purposes)	
2	Approximately how long, in minutes, did it take for you to install the power strip?	
3	If you failed to install your power strip, what was the reason?	(*Merged into question No.12*)
4	Where did you install or setup the sensor module? (Please select multiple options if you use the room for other purposes)	
5	Approximately how long, in minutes, did it take for you to install the sensor module?	
6	If you failed to install the smart home sensor module, what was the reason?	(*Merged into question No.12*)
7	Where did you install or setup the Google Assistant device? (Please select multiple options if you use the room for other purposes)	(*Removed*)
8	Approximately how long, in minutes, did it take for you to install the Google Assistant device?	(*Removed*)
9	If you failed to install the Google Assistant device, what was the reason?	(*Removed*)
10	-	Where did you install or setup the dashboard tablet?(Please select multiple options if you use the room for other purposes)
11	-	Approximately how long, in minutes, did it take for you to install the dashboard tablet?
12	-	What kinds of issues, if any, did you experience during the installation process? Please describe.
13	Please rate how easy or difficult it was to install the power strip. (1: Extremely difficult, 2: Somewhat difficult, 3. Neutral, 4: Somewhat easy, 5: Extremely easy)	
14	Please rate how easy or difficult it was to install the sensor module. (1: Extremely difficult, 2: Somewhat difficult, 3. Neutral, 4: Somewhat easy, 5: Extremely easy)	

15	Please rate how easy or difficult it was to install the Google Assistant device. (1: Extremely difficult, 2: Somewhat difficult, 3. Neutral, 4: Somewhat easy, 5: Extremely easy)	(*Removed*)
16	-	Please rate how easy or difficult it was to install the tablet. (1: Extremely difficult, 2: Somewhat difficult, 3. Neutral, 4: Somewhat easy, 5: Extremely easy)
17	Overall, how easy of difficult was it to follow the instruction tutorial? (1: Extremely difficult, 2: Somewhat difficult, 3. Neutral, 4: Somewhat easy, 5: Extremely easy)	
18	Overall, how easy or difficult was the entire installation process? (1: Extremely difficult, 2: Somewhat difficult, 3. Neutral, 4: Somewhat easy, 5: Extremely easy)	
19	-	Overall, how helpful do you think the instruction tutorial was in completing the installation process? (1: Extremely difficult, 2: Somewhat difficult, 3. Neutral, 4: Somewhat easy, 5: Extremely easy)
20	Did you receive any help with installing the sensors?	(*Removed*)
21	If you received any help, from whom did you receive the help?	(*Removed*)
22	Please indicate how you felt about the amount of time you spent on the installation process. (1: Very quick, 2: Fairly quick, 3. Neither quick nor time consuming, 4: Fairly time consuming, 5: Very time consuming)	
23	How much do you agree or disagree with the following statements regarding the home technology kit? "I think the home technology kit _________" (1: Strongly disagree, 2: Disagree, 3. Neutral, 4: Agree, 5: Strongly agree)	
23.1	May put my privacy at risk	
23.2	-	Is trustworthy
23.3	-	Will be practically useful
23.4	-	Will be easy to use
23.5	-	Will seamlessly work with other systems I have
24	If you answered 4 or 5 to question 23.1, why would you be concerned with your privacy using the installed devices?	(*Removed*)
25	Overall, how satisfied or dissatisfied are you with the installation process? (1: Not satisfied at all, 2: A little bit satisfied, 3: Somewhat satisfied, 4: Very satisfied)	
26	-	Based on your impressions until now, how satisfied or dissatisfied are you with the home technology kit? (1: Not satisfied at all, 2: A little bit satisfied, 3: Somewhat satisfied, 4: Very satisfied)
27	-	Please use the space below to let us know about any other comments or suggestions you have regarding the installation of the home technology kit.

6 EVALUATION RESULTS

Overall, the success of self-installation was uniform across participants of different demographic characteristics. The participants were able to install all components without any on-site technical support from the research team. However, one participant in her 50s has gone through the installation process with her husband who is also in his 50s. Three other participants in their 60s and 80s received help from the research team via email about the accuracy of sensor data, the pairing the sensor module to their WiFi network, and adjustment of the small font size on the Android tablet. One another participant in his 80s asked for help through a video call to complete the sensor module's WiFi pairing issue. Two sensor modules were partially damaged in the mail, which might be a larger concern at scale, but it did not affect the installation procedure in this study. One participant was unable to install the power strip due to the WiFi security setup in a campus housing the participant lived in.

In terms of location, *living room or family room* was the most popular spot for installing the devices. More than half of the participants installed the power strip, sensor module, and Android tablet in their living rooms or family rooms; no participant installed the Google Assistant device in the living room. The next popular location was *home office*, followed by *bedroom*, *dining room*, and *kitchen*, although no participant installed any devices in their *bathroom*.

6.1 Ease and duration of self-installation

Figure 10 illustrates the responses for the questions around the ease of the self-installation procedure and the user instruction of the home technology kit (questions 13 - 18 in Table 3). In the pilot study, no participant reported a negative response (i.e., difficult or very difficult) for the questions, and *'Extremely easy'* was the most frequent response to four questions, implying that the self-installation was easy in general and it did not give frustration to the participants. Especially, the sensor module was evaluated as the easiest part to install, with all but one participants reporting that its installation was very easy. On the other hand, the power strip had the least number of positive responses among all parts of the study kit. While the power strip still received generally positive feedback, the relatively neutral assessment suggests the need to improve the user interaction and instruction for this component in order to enhance the overall user experience.

On the other hand, in the field study, most participants answered that the installation procedure was very easy, except the sensor module. All the participants, including older ones (50+ years old), considered installing the power strip extremely easy in the field study. In the first round with five participants, the sensor module was the bottleneck, and three participants considered its installation difficult. As the result, it harmed the overall ease of installation. From answers for question 12, *'What kinds of issues, if any, did you experience during the installation process?'*, it was found that the QR code-based pairing of the Particle IoT board on the sensor module was not working well due to the low resolution of the camera on the deployed Android tablet, and the continuous trials and failures frustrated the participants (see participants' feedback in Figure 11).

Such flaw was fixed in the second round with seven participants by changing the installation procedure. The QR code-based pairing was done by the research team members before its deployment, and the participants were only asked to reconnect the paired device to their WiFi. This refinement improved the perceived ease of installation of the sensor module in the second round. However, the sensor module was considered more difficult to install than it was in the pilot study. Only 57% (n=4) of the participants considered the installation *somewhat easy* in the second round of the field study, while 87.5% (n=7) and 12.5% (n=1) considered it *extremely easy* and *somewhat easy* in the pilot study, respectively. Such degradation was attributed to inclusion of a broader participant base, including people in their 80s. In the survey, we found that older participants had difficulties

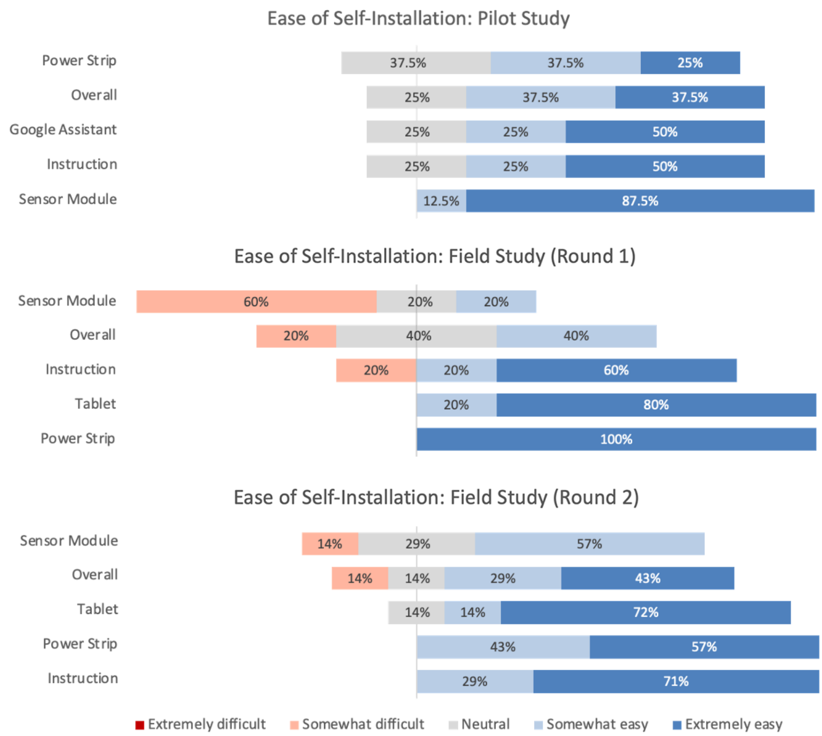


Fig. 10. Evaluation of the ease of self-installation (% of respondents; $N_{pilot} = 8, N_{field\_r1} = 5, N_{field\_r2} = 7$)

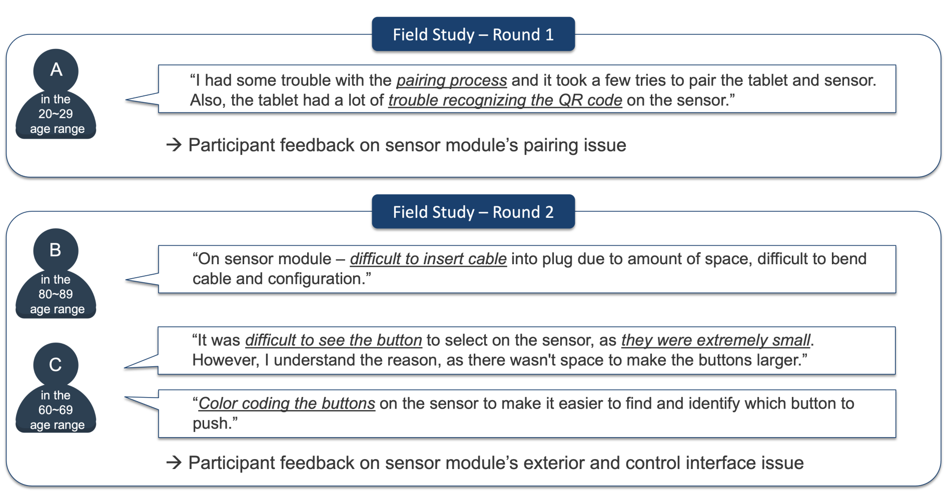


Fig. 11. Participants' feedback on sensor module during the field study (Round 1 and Round 2)

controlling small hardware interface, suggesting the need to improve the sensor module's exterior and control interface design. Figure 11 shows participants' feedback and suggestion regarding this issue.

Differences in the perceived ease of installation between the younger participants and the older participants are clearly observed in Figure 12. Figure 12 shows results around perceived ease of installation for all twenty participants, as well as for subsets of participants divided by age. Overall, the perceived ease of self-installation by older participants (50+ years old) is lower than younger participants in all components. Especially, perceived ease of installation scores for the sensor module and the overall procedure reported by older participants were in the middle of the Likert scale, neither easy, nor difficult. The installation duration analysis in Figure 13 suggests a possible explanation for such differences. On average, sum of duration taken by younger participants to install the delivered components was 39.4 minutes. On the other hand, that of older participants is 61.8 minutes, which is 56.9% longer than younger participants. This clear gap could contribute to the difference between different age groups in the perceived easiness. It is also noticeable that the variance of older participants' installation duration in the sensor module is much greater than variances in the other measures. This suggests that, unlike younger participants, older participants' perception easily diverged in response to the sensor module's exterior and the device pairing procedure.

To analyze the impact of participants' technology-related background on the perceived ease of installation of each module, Spearman's correlation coefficients between field study participants' responses to five screening questions (see Figure 8) and those to the easiness questions in the post-installation questionnaire (questions 13 - 18 in Table 3) were computed (Figure 14). From the correlation coefficient values, it is shown that levels of participants' interest in learning new technologies and tendency to early adopt new technologies generally affect the perceived easiness

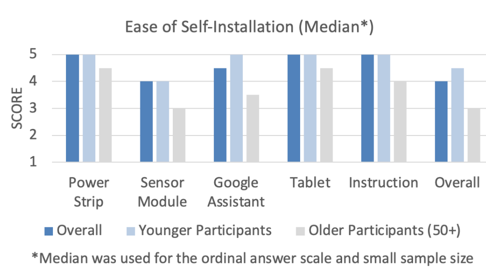
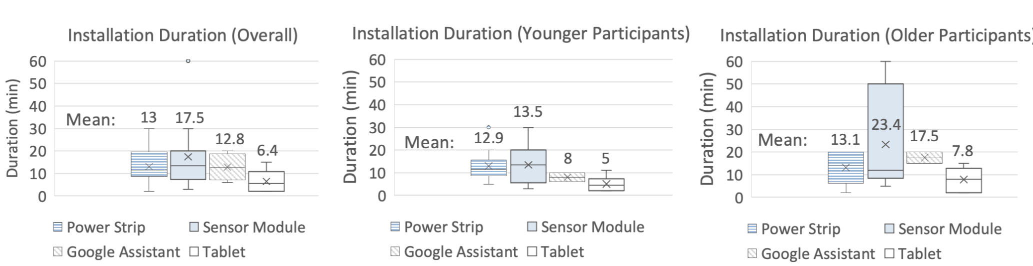


Fig. 12. Ease of installation (1: Extremely difficult - 5: Extremely easy)



(a) Overall (b) Younger Participants (c) Older Participants (50+)

Fig. 13. Self-Installation Duration

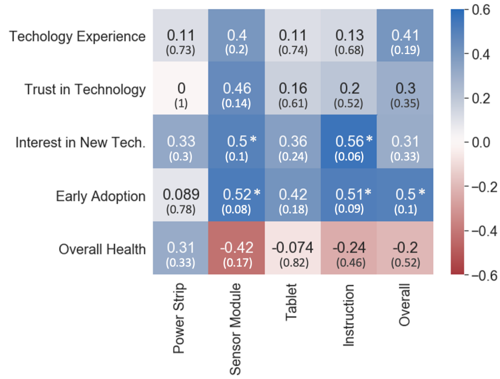


Fig. 14. Spearman's correlation coefficients between the technology-related background and the ease of installation
(*p-values are in parentheses. *: p* $\leq$ .1)

more strongly than other factors. This implies that the more a participant was interested in technology, the easier they considered the installation process. Especially, the perceived ease of the sensor module's installation was affected by not only interest and trust in new technologies but also by technology experience, tendency to early adopt technologies, and overall health. This finding is in line with the previous survey result, presenting that older participants with a low level of technological literacy had difficulties to complete the installation of the sensor module. While statistical significance of this association is not strong given a small sample size - only five p-values for the correlation coefficients are less than or equal to 0.1 - it suggests a possible relationship.

6.2 Perceived Privacy

Figure 15 shows twelve field study participants' responses to the questions about the perceived level of privacy concerns and relevant variables (questions 23.1 - 23.5 in Table 3). Overall, the result shows mixed responses about the perceived privacy level, while a little more participants answered that the prototype kit might put their privacy at risk to a certain extent. Participants' feedback also included mixed opinions about the privacy concerns as shown in Figure 17. When the consent form was explained to the participants in the screening interviews, it was observed that the participants had a high trust level on our institute's strict IRB protocols and restrictions. Such a high trust would be reflected to the corresponding responses to the trustworthiness question and make the participants willing to provide their smart home data without any objections despite their mixed responses to the perceived privacy question. In addition, majority of participants responded that the prototype kit would be practically useful, easy to use, and work with other systems they already have. This result supports the perceived usefulness and usability of the prototype kit. A previous finding [57] presents that users' desires for the usefulness, such as convenience and connectedness, dictate their privacy-related behaviors. Associated with this finding, the results can be interpreted such that the perceived usefulness of the kit would alleviate the privacy concerns of the research participants, while this statement requires a further investigation.

It was also analyzed how age would affect the perceived privacy level. Figure 16 illustrates twenty responses to question 23.1 from the pilot and field studies, as well as for subsets of participants divided by age. Overall, the portion of younger participants who answered that the home technology kit may not put their privacy at risk was higher than that of older participants, while both participant

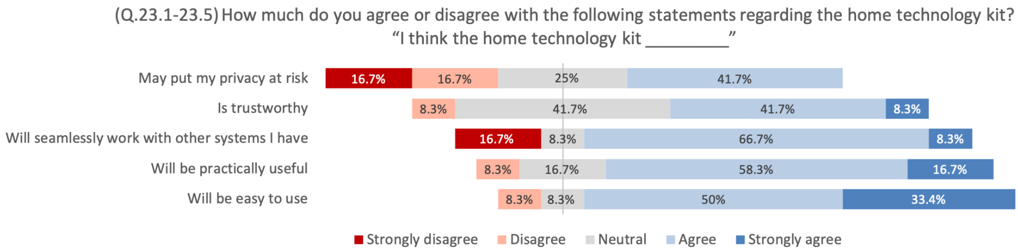


Fig. 15. Perceived level of privacy concerns (% of respondents)

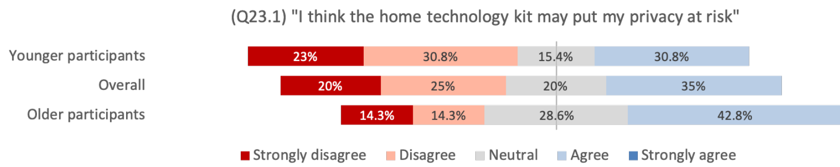


Fig. 16. Perceived level of privacy concerns by younger and older participants (% of respondents)

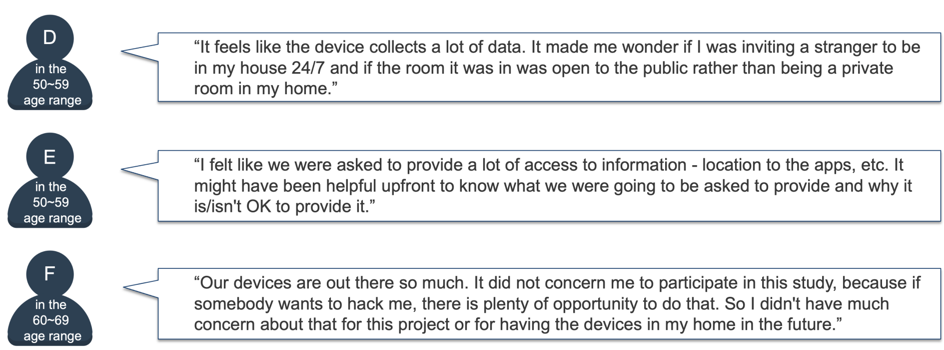


Fig. 17. Participants' feedback with mixed opinions on privacy

groups show mixed responses. This result is in line with previous findings [14, 38], presenting that younger people express more positive and confident attitudes toward data management and their ability to prevent possible data misuse while the privacy is a barrier for older adults' adoption of smart home technologies.

6.3 Satisfaction Level

Although the field study had design issues and some participants had trouble around them, the survey results show that participants were generally satisfied with the smart home prototype kit and installation process. Figure 18 illustrates answers for question 25 and 26. Upon the smart home prototype kit, all participants except two answered that they were satisfied. Two participants who answered *A little bit satisfied* were those who had trouble with the sensor module. The satisfaction level of the overall installation process was even higher than that of the smart home prototype kit. The instruction document contributed to this high level of satisfaction as shown in Figure 19. 66% of the participants answered that the instruction document was extremely helpful in completing

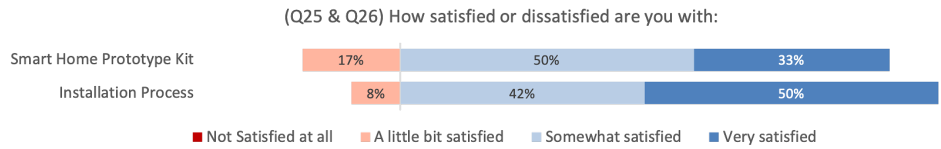


Fig. 18. Satisfaction level of the installation process and prototype kit (% of respondents)

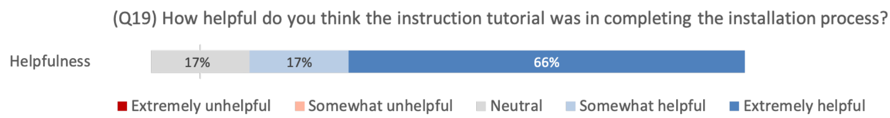


Fig. 19. Helpfulness of the instruction tutorial in completing the installation process (% of respondents)

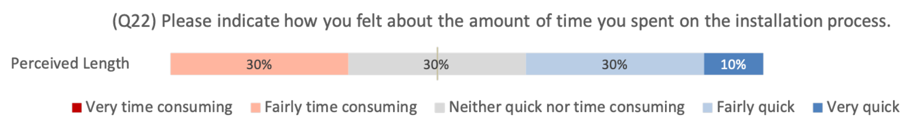


Fig. 20. Perceived length of self-installation process (% of respondents)

the installation process, and no one answered that the instruction was unhelpful. One of the participants said that *"My compliments on the instructions. Nicely done, step by step, clear and photos were awesome. Nice touch putting the email login info at the top right corner. This is all thinking out loud but it may reflect some elements of what the general public might be thinking too."*

Improving the installation process or design of the prototype kit modules to reduce the installation duration would further enhance the satisfaction level. Figure 20 shows the perceived length of the installation process by the participants. Only 40% of the participants answered that the installation process was fairly or very quick while 30% perceived it time consuming. The results in Figure 13 and aforementioned participant feedback suggest that there is a large room for improvement in the installation duration of the sensor module.

6.4 Discussion

While smart home technologies have the potential to enable a more convenient lifestyle and improve connections between people, a large-scale evaluation of its core technologies has been performed in a limited setup and hardly scaled out due to the need for experts' in-person visit to set up a smart home testbed. To this end, this study presented an easy-to-install smart home prototype and its scalable deployment and installation procedures. Our findings from its evaluation reveal that a user-centered design of the smart home platform incorporating the critical requirements of interoperability, privacy preservation, cost efficiency, and remote operation can remove the needs of experts' in-person visit for smart home testbed construction. A simple and user-friendly design of the prototype kit's deployment and installation procedure was critical to enable the participants to complete the self-installation without an on-site technical support. The participants' overall satisfaction level of the employed smart home technology kit and the self-installation procedure was high, envisioning that smart home research can be conducted at scale and in a cost efficient manner.

However, the findings also reveal that the participants' perceived ease of the self-installation is affected by individual differences in age, technology experience, and interest in new technologies. The employment of multiple data protection methods could not resolve the privacy concerns completely. Sensing fidelity in terms of data quality is another remaining issue that needs to be investigated further. We next reflect upon the potential future work for researchers, developers, and designers. We describe how we might make the self-installation process easier and demonstrate the application of the proposed method to smart home research use cases. We also present novel challenges and suggestions regarding privacy concerns, sensing fidelity, promising research use cases, and cooperative contribution for the smart home research community.

6.4.1 Further improvement for the instruction document and easier self-installation. The correlation between the participants' interest in learning or adopting new technologies and the perceived ease of installation presented in Section 6.1 reveals a limitation of this study. The correlation seems to be natural and inevitable. However, considering that minimizing such correlations by enabling people with a low level of interest in learning or adopting new technologies to complete the installation process with the minimum difficulty (i.e., making all the responses *'extremely easy'*) is this study's goal, the presence of meaningful correlations suggests that a further investigation and design improvement need to be established to reduce them. Especially, the installation process of or the instruction document for the sensor module need to be redesigned more carefully than other components. Inclusion of more diverse participants in the field study revealed unexpected pain points, suggesting that future studies with more participants will facilitate the establishment of a better user experience. A further confirmatory study with a larger and more targeted samples, including older adults with less technological experience and low trust in technologies, will be conducted as a future work to verify the findings in this work with statistical significance.

6.4.2 Privacy preservation and data protection. Many past studies have tried to reveal the nature of privacy in the smart home context [6] and analyze how users perceive their privacy in smart home [57]. According to the Contextual Integrity (CI) framework [6, 42], privacy is a function of information flows and its appropriateness is contextual, not static, to five norms or parameters: (1) the sender, (2) the recipient, (3) the attribute or type, (4) the subject, and (5) a transmission principle of the information. Based on this framework, it is worth discussing whether the proposed research method complies with the "appropriateness" of information flows and if the method is acceptable by users.

In this study, all the information about the sender, recipient, attributes, and subject of the smart home data were informed to the participants before the data collection started. In addition, all data was encrypted before its transmission and stored in a password-protected secure cloud server. An Institutional Review Board (IRB) has reviewed and approved the study, and a consent form(s) was signed by the participant(s) using DocuSign before the study started. Researchers and participants reviewed the consent form together by having a video conference meeting before the study started to let the participants clearly understand what type of data is collected, how and where their data is collected and stored, who has access to the data, and how it is going to be used in target use case scenarios during the study. During the study, participants could keep track of which data has been collected using the dashboard application. According to the acceptability score analysis of the smart home IoT privacy study [6], our entire practice is highly acceptable by the users. In addition, the participants showed a high trust level on our institute's strict IRB protocols and restrictions despite their mixed responses to the questions asking about the perceived privacy (Figure 15).

However, the participant's perception could change if any condition of the five norms changes, and this study does not include additional exploration of the perceived privacy and its acceptability in different use cases. For example, if a participant's care recipient, not the participant, is the subject of the collected data, the level of privacy concerns may be affected depending on their relationship or the care recipient's attitude towards privacy. Privacy concerns with daily activity data and medical information should also be different. To mitigate potential limitations of the proposed method due to such variants, it is vital to identify possible requirement changes by any modification of the five CI framework norms and refine the proposed method including the smart home prototype architecture. To this end, we plan to conduct semi-structured interviews with our field study participants to further discuss those topics with different use cases as our next step. At the same time, we plan to refine the proposed prototype architecture so that it can accommodate such requirement changes dynamically by decoupling the business logic (i.e., requirement specification) from the system behavior. The business logic will be translated into multiple system parameters including privacy, and those parameters will be used to tune the smart home system's behavior accordingly.

6.4.3 Research applicability. The smart home has been considered as a platform of automated services and their underlying research activities [17]. Therefore, it is crucial to verify whether the prototype can facilitate current and future smart home research, in addition to considering the user experience. Two popular research scenarios related to the three use cases, *safety and security*, *caregiving needs*, and *home energy and environment control*, were developed by using the data collected from the pilot study to demonstrate its practicality.

User occupancy detection is one of the most popular research topics in smart home domain. It can be used to detect suspicious in-home movement during the resident's absence for a safety and security use case. It can also be used to reduce electricity usage by shutting off standby energy consumption while the the room is not occupied by the user. To demonstrate that the proposed platform can be used for such a popular research use case, we developed a change point detection (CPD)-based occupancy detection algorithm [51] using the collected motion, sound, and brightness sensor data. Figure 21 illustrates the overall pipeline through which smart home timeseries data is associated with occupancy labels that had been manually annotated by participants using Google Assistant devices and IFTTT applets. The CPD algorithm consumes the labeled dataset to detect user occupancy, and the result is visualized on Jupyter Notebook.

Activity recognition has been considered as the most important technique for caregiving and safety use cases, and many machine learning models have been presented to *recognize user activities* in a smart home or other types of smart spaces using multivariate sensor data [5, 8, 9, 28, 55]. To promptly demonstrate this activity recognition research scenario using the proposed platform and pipeline, we collected the sensor data from a research member's (i.e., user) house for one month.

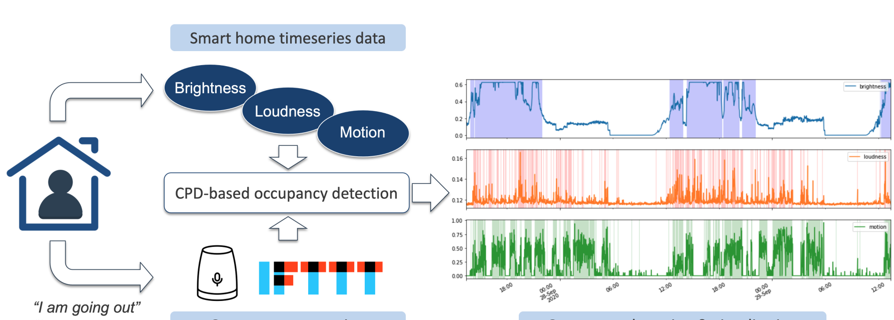


Fig. 21. CPD-based user occupancy detection pipeline

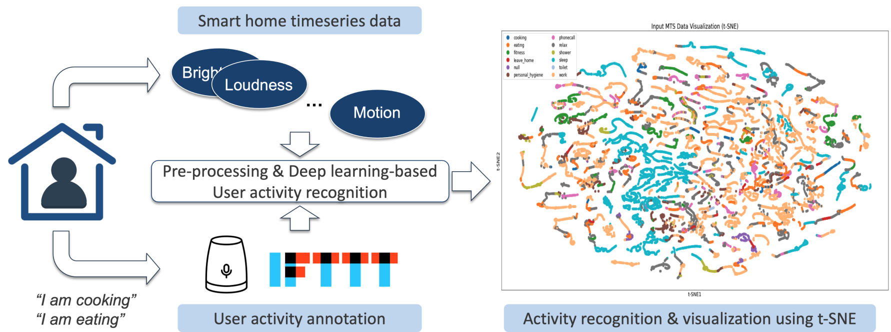


Fig. 22. Deep learning-based user activity recognition pipeline

Figure 22 illustrates the overall pipeline of the implemented scenario. The user told the Google Assistant device what activity was finished or started using twelve activity labels (e.g., Cook, Eat, Sleep) used in the CASAS smart home project [28]. Each activity label was transmitted via the IFTTT applet and associated with collected sensor data in the database server. The preprocessed (e.g., resampling, normalization) data was used by various deep learning models, including 1D-CNN, 2D-CNN, LSTM, and GRU, and visualized using the Principal Component Analysis (PCA) and t-SNE.

Under these sample scenarios, the system prototypes built with the proposed platform and pipeline were able to collect and analyze necessary data, thus demonstrating that it could effectively facilitate smart home research at scale. Although no research demonstration beyond data visualization has been conducted upon the electricity usage data collected from the power strip devices (Figure 3c), the data can be used for many scenarios including occupancy detection [27] and activity-based energy saving [35]; the device provides APIs for turning on and off its power outlets. Removing the needs for in-home visits for the home network configuration and system setup can incredibly enhance not only the quantity but also the quality of smart home dataset. Considering that CASAS dataset [28] is the only large dataset that has been used across world wide smart home researchers as the pseudo-standard, the proposed platform and pipeline can facilitate crowsourced dataset generation as a collaborative effort of multiple research groups as of the *IoT Inspector* in home security and privacy domain. As the result, it can facilitate the adoption of more sophisticated AI and machine learning methods accordingly.

6.4.4 Sensing Fidelity. While this study focuses on devising and evaluating a scalable smart home research method, it is worth discussing whether the sensing fidelity achieved by the proposed method is appropriate for smart home use cases including the envisioned ones in Section 6.4.3. This question becomes more critical especially when the installation of the sensor modules are completely up to the participants who have no expert knowledge. Besides the accuracy and type of each sensor, positioning and amount of the sensor module may affect the sensing fidelity, and eventually, the quality of the research outcomes. Even though the instruction document in our field study included guideline pages for placing or positioning each device module, without a carefully-designed fidelity measurement tool, it was challenging to ensure that a participant's installation is perfect and the quality of collected data from multiple households are evenly high. The Radio Frequency (RF)-based sensing methods, discussed in Section 2.4, could be more robust and alleviate the participant-specific variation. However, it is still experimental and delivers less semantic information compared to the proposed sensor module. Deploying more sensor modules could mitigate the sensing fidelity issue as many field study participants wanted for the better awareness of their homes. CASAS smart home testbed [28] also deployed tens of binary motion sensors over the entire house. In this case, it will be worth exploring how many units can achieve appropriate sensor fidelity for various smart home applications with the privacy preservation and minimum cost.

6.4.5 Companionship with Smart Speakers. Cyber-physical companionship with a smart home or in-home devices has been recently discussed or devised in multiple past studies. FakhrHosseini et al. [17] presented a taxonomy of technology-integrated homes and suggested that the highest level of autonomy in a smart home platform would enable homes to provide meaningful companionship. Pereyda et al. [45] presented a robot/smart home partnership to support a user's daily activities. Considering the dialogue-based natural interaction, smart speakers have been considered as the most promising in-home device to achieve such a companionship. However, rather than devising new interaction or adoption models of smart speakers in smart home domain, people have mainly focused on the privacy issue in association with the use of smart speakers in home environments [2, 30]. Especially, understanding possible threats of and establishing privacy norms for smart speakers have been heavily discussed.

Besides the privacy concerns, smart speakers have potentials for various use cases throughout the entire smart home research pipeline, and it is important to envision promising use cases and discuss how they can replace the current research topics and methods. For example, in this study, the consent form was signed by the participants only once at the beginning of the pilot or field studies. However, participants often sent us an email to ask study-related questions such as whether they have to change a module's location when they have visitors. In such cases, integrating smart speakers for dynamic inquiry or consent would be a useful application for both participants and researchers. Besides, developing autonomous smart home systems using distributed systems and machine learning principles have been the most popular research topics [18, 47]. However, how to achieve resilience from system failures in smart home-user interactions have not been seriously dealt with yet. Smart speakers would be the most promising and attractive methods for smart home researchers because they can converse with users to recognize the failure and reflect it to the smart home intelligence and its back-end system. Obviously, successful inclusion of such noble use cases will replace many current research methods and suggests new breakthroughs in the smart home research community.

6.4.6 Contribution to Cooperative Smart Home Research. One of the most promising contribution that this work can deliver to the smart home research community and industry is to facilitate cooperative smart home research. The rapid growth of the artificial intelligence and machine learning community has been backed up by the cooperative effort to create and share a large scale standard dataset for many different tasks, such as ImageNet [46], CIFAR-100 [29], MNIST [32], and Youtube-8m [3]. On the other hand, smart home research community has only a small number of publicly available datasets, such as CASAS [28], Casteren [52], Ordonez [43]. Among those datasets, only CASAS has been widely adopted for the application of modern machine learning techniques to smart home use cases due to the small size of the datasets. Many reasons could affect the lack of cooperative effort to establish a large scale smart home dataset, and it has been continuously recognized in the community that the testbed construction and maintenance procedure is costly and demanding. To this end, we envision that the methods and findings from this work may initiate such a cooperative effort. For the future work, we plan to release our repository and documentations as an open source project so that any members in the research community can conveniently reproduce our practices and refine them. We also plan to conduct a larger-scale long-term evaluation across country from which we can establish a practically useful public dataset of smart home usage and user behavior.

7 CONCLUSION AND FUTURE RESEARCH

This case study addressed scalability issues in the traditional smart home research as well as the increased need for safer research procedures brought by the COVID-19 pandemic. To facilitate a scalable and safe smart home research, a smart home platform prototype was developed and tested for a low-cost implementation, remote support, and user-driven installation. Pilot and field studies were conducted to evaluate the proposed prototype, during which the prototype kits were sent to participants who self-installed them in their homes. The evaluation revealed that the prototype design and the installation process facilitated a seamless initial experience with very little confusion, while mixed responses about privacy concerns remain as future work.

Next iterations of the prototype development, design, and evaluation will address issues identified from this study by 1) expanding the participant pool to ensure the diversity of participants and provide statistical significance, 2) improving the instruction document with examples and clear guidelines, and 3) adopting a diversified and targeted approach to better demonstrate various use cases. Finally, as an extension of this work, the real-life data gathered in this study can be contributed to the cooperative effort of the smart home research community to establish a large scale smart home dataset.

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