# User Involvement in Training Smart Home Agents

## Increasing Perceived Control and Understanding


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## ABSTRACT

Smart home systems contain plenty of features that enhance wellbeing in everyday life through artificial intelligence (AI). However, many users feel insecure because they do not understand the AI's functionality and do not feel they are in control of it. Combining technical, psychological and philosophical views on AI, we rethink smart homes as interactive systems where users can partake in an intelligent agent's learning. Parallel to the goals of explainable AI (XAI), we explored the possibility of user involvement in supervised learning of the smart home to have a first approach to improve acceptance, support subjective understanding and increase perceived control. In this work, we conducted two studies: In an online pre-study, we asked participants about their attitude towards teaching AI via a questionnaire. In the main study, we performed a Wizard of Oz laboratory experiment with human participants, where participants spent time in a prototypical smart home and taught activity recognition to the intelligent agent through supervised learning based on the user's behaviour. We found that involvement in the AI's learning phase enhanced the users' feeling of control, perceived understanding and perceived usefulness of AI in general. The participants reported positive attitudes towards training a smart home AI and found the process understandable and controllable. We suggest that involving the user in the learning phase could lead to better personalisation and increased understanding and control by users of intelligent agents for smart home automation.



## CCS CONCEPTS

• **Human-centered computing** → *Human computer interaction (HCI)*; *Empirical studies in HCI*.

## KEYWORDS

human-agent interaction, smart homes, supervised learning, participation





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## 1 INTRODUCTION

For quite some time, many smart home systems have been appearing on the market. Such systems entail technology designed to make inhabitants' lives easier and enhance their wellbeing at home [10, 18, 28], often through intelligent agents operating home appliances [17, 39]. Users appreciate the convenience, aesthetics, and entertainment functions of smart homes [52], and even older adults with little technical experience deem them useful [11]. However, some issues have curtailed people's acceptance and interest in using such technologies. Control and perceived control have been major obstacles to acceptance and trust in smart home agents [20, 37, 41, 59]. While "control" means the objective amount of control an individual has over the environment or an outcome, "perceived control" describes the subjective beliefs about the amount of control the individual has [38]. "Keep users in control" is known as one of the "Eight Golden Rules of Interface Design" [49]. If users feel a lack of control over their IOT system, it negatively influences the ease of use and can lead them to refrain from using the system [3, 37, 57]. Reasons for perceived lack of control over technology can be manifold, including deficient comprehensibility and too few personalisation options [50]. This might especially affect technologies that are still new to users [50]. Therefore, understanding how a smart home agent works is an important factor for the feeling of control and, consequently, usage intention [41]. Though users might trade security for comfort, many of them also worry about privacy, being monitored or unclear usage of the collected data [7, 11, 27, 59].

Acceptance, trust and control are also central desiderata discussed in the rising research area of Explainable Artificial Intelligence (XAI) [5, 9, 48]. The goal of XAI is to increase stakeholders' understanding of a software system to mitigate the negative effects of its often opaque nature, which includes potential users' rejection of the system [cf. 26]. While the idea of XAI is typically meant to include all potential stakeholders, most current XAI approaches (e.g.

LIME [40], TCAV [23], SHAP [33]) are primarily suitable for increasing the understanding of computer scientists. Increasing the understanding of laypeople will most likely require approaches that are psychologically, philosophically and sociologically informed [34].

A well-established way to make technology user-friendly is to let users participate in its development. Co-design [13, 43] and participatory design [4, 51] are approaches which involve users in the creation of new technology. By involving them, users become active participants in control, empowering them [6]. Co-creating a technology or certain functions of it can thus improve their sense of agency [31]. Research found that users get a better understanding of technology-based services if they are involved in their creation [44].

Aside from the possible User Experience benefit, user involvement has the potential to increase the performance of smart home systems. Some skills of intelligent homes, like the recognition of user activities, appear to be very individual and need to be highly personalized. Therefore, it is often not feasible to generalize by learning from previously gathered user data; instead, matching the system to the specific living space and behaviours of the user is necessary. Other authors have pointed out the need for data annotation by users and have already started to design measures to facilitate annotation for users in activity recognition applications [1]. By including the human-in-the-loop, more fine-grained systems can be reached [46].

We propose that by including the user in the loop of the intelligent agent's learning, both the performance of smart living environments could be improved and user wellbeing enhanced through a better feeling of understanding and control. In our idea, co-creation takes place by users as trainers of an activity recognition system in a supervised learning approach, in which the user actively provides the training data and labels. By doing so, the user also decides which activities the agent should learn to recognize and which not. This puts the focus on the input of (user) data and its relevance in the context of explainability instead of just addressing the functioning of the AI with data already provided. Instead of understanding co-creation only in the sense of joint development of applications or design by users and developers [32], e.g., in workshops [24], we expand it to the interaction of users and intelligent agents.

In this work, we conducted two studies: In a pre-study, we explored users' perception of training a smart home AI in an online study, and in the main study, we performed a Wizard of Oz laboratory experiment with participants. With this work, we contribute:

(1) A new example for user empowerment by participation in an intelligent agent's training.
(2) A first exploration of the role of the data input phase for user experience of AI
(3) Measurements of users' perceptions of the possibility to be involved in the supervised learning of artificial intelligence
(4) An Interview of potential users about their self-reported willingness to participate in agent training

We found that users' feelings of control, perceived understanding and perception of the usefulness of AI were increased after the training process. It also had a positive impact on their privacy perception of smart homes. Users perceived the process under our laboratory conditions as understandable and controllable and reported a high willingness to train a real AI in such a way to gain smart home functionalities for themselves or their relatives. Possible enhanced personalisation and privacy played a role in the appropriateness of the approach, according to users.

In what follows, Section 2 gives an overview of related work. Section 3 introduces our pre-study before describing our main study and results in Section 4. Section 5 discusses our findings. Supplementary material to this paper can be found at https://osf.io/kxhj3.

## 2 RELATED WORK

*Role of understanding and control in AI and smart homes.* In their study about user acceptance in smart homes, Park et al. [37] found that perceived control influences perceived ease of use and thus perceived usefulness and attitude toward IoT smart home technology, which in turn influences intention to use. Tabassum et al. [53] summarize the participants' perception of data practices: "they base their understanding of what data is collected on their experiences and interaction with the devices." The authors also described users' feelings that once their data is collected, it is beyond their control. In conclusion, they recommend that companies provide more transparency and control to users. Correspondingly, a field study about activity logging in smartphones found that participants agreed to this kind of monitoring as long as they had control over what kind of data was logged and were able to delete it later [21]. Other smart home researchers, who have also identified "lack of control" as a challenge, suggest a training phase involving users as a possible solution [57]. However, they doubted that users would be interested in a training mode but did not actually question the participants about this. We suggest that willingness to train the smart home depends on the application, its goal and how much involvement is needed. Our research, therefore, should also clarify the users' willingness to engage in the learning phases of intelligent systems. In his proposed AI paradigm, Zanzotto [58] also noted the importance for everyone involved of knowing which training data has been the reason for an AI decision, which underlines the relevance of the data input on which we focus in this research. A study about ethical concerns towards robots used in the care of older adults used a co-creation approach, where participants decided on the activities of daily living in which a robot should help [42]. This approach has some similarity to ours, which also gives users the possibility to decide which activities the AI should be able to recognize and thus be able to act on.

*Current smart home technology.* In intelligent smart home devices that are currently established on the market and most familiar to the average user, the system behaviour is mostly predefined or rule-based. There is hardly any possibility for user interaction with the underlying algorithms. For Google Home, custom voice commands can be added through a third-party app [19], but the defined behaviour is fixed and no learning takes place. Amazon Echo offers more of a learning approach, but only for speech recognition, where the user can add more examples of their voice to improve the speech recognition algorithm [56]. If learning from user behaviour plays a role in current smart home applications, this is mostly done passively today, that is, without active user intervention [12, 54].

*Approaches to increase understanding and control in smart homes.* A model to clarify misunderstandings between smart homes and users was created by Despouys et al. [16]. Using the proposed system, the user can ask the smart home for the reasons behind an action or request and receive a causal explanation. This way, the solution features explainability for understanding the functioning of a smart home with a human-like interaction. Lakbir et al. [25] imagined a smart home agent that provides information about its devices through gamification, is able to answer questions about data usage and provides the possibility for the user to restrain data collection. The intervention user interface paradigm [46] states that, although there is no need for a user to constantly monitor an autonomous system, there is a need to be able to intervene when an exception occurs. If the user does not want the system to pursue its normal behaviour or when the system is not working as intended, they intervene in a running ML-based system by declaring exceptions [20, 29, 46]. This approach is designed to improve the user experience by putting the user back in control of the technology. It emphasises the importance of user control and understanding of processes for users as well as the ability to collaborate with the system.

*User involvement in smart home learning.* Research studies exist where the commitment of the participants is used for training ML algorithms. Users label their activities for supervised learning [55], intervene in reinforcement learning [45], or have their behaviour analyzed [2]. Unfortunately, none of these works describe the participants' opinions or the users' experience in these learning phases. While the use of facial feedback to enhance learning in robots was considered [30], it was not assessed how users would like to provide such feedback. In the context of activity recognition, it is common to use labels provided by users [8, 35], but their perception of doing that is rarely discussed and was never properly evaluated. Apart from these few examples in the literature, which lack user experience measurements, researched smart home systems mostly rely on learning through monitoring user behaviour. However, when the user is merely a passive target and does not actively and willingly engage in the training, no real participation occurs [36].

## 3 PRE-STUDY

For a first glance at people's perception of user involvement in smart home learning, we conducted a study via SoSciSurvey. Participants were recruited via social networks (SN), forums and using snowball effects where participants forwarded the link. The study was conducted from 19th May to 30th July 2020 in German with participants from Germany. Here we tried a video prototyping method to assess its feasibility for increasing users' understanding. We realized this by showing participants animated videos of a person interacting with a smart home. The online study was preregistered at https://osf.io/hg56x.

### 3.1 Method

First, participants completed the TA-EG questionnaire on technology affinity [22]. Then they were informed about the goal of the study and shown an animated video with an example of how a smart home agent works: A resident enters a living room, sits on a sofa and turns on the television. All lights are switched off automatically by the agent without the resident giving any command. When he gets up again and grabs a book to read, the lights are turned on again. They are then told that the smart home must first be trained to recognize activities in this way and react accordingly.

After this, they were shown another video about a possible learning phase, which presented a supervised learning (SL) approach: In this video, the resident is sitting in the same room as in the previous video, first watching TV and later reading a book. Whenever he starts or stops one of these activities, he uses a voice command to tell the smart home what he is doing, for example, "Smart home, I (no longer) watch TV". The video was accompanied by a short explanation of how the smart home is supposed to learn from such information. Participants were then questioned about the smart home system they saw in the video. Questions and instructions can be found at https://osf.io/pjt4y. The questions consisted of the scales Attractiveness, Efficiency, Perspicuity and Stimulation of the User Experience Questionnaire (UEQ) questionnaire [47]. In addition, there were 5 questions on a 5-point Likert scale about the understandability of how the smart home learns, perceived usefulness, impracticability (inverted item), perceived controllability and general liking.

Participants were then shown a third video with another approach using reinforcement learning (RL), accompanied by a brief explanation. In this video, the smart home has already gained the functionality to adjust the light and behaves correctly and incorrectly. Depending on the behaviour, the system is dismissed or reinforced by the user. When the user enters the room and sits on the sofa, the light is switched off, and the user says "Smart Home - Wrong", whereupon the system corrects its behaviour by switching the light back on. Later, the smart home agent sets the light correctly, and the user gives a voice command feedback that the behaviour was correct. After the third video, the participants were asked the same questions as after the first.

Finally, socio-demographic questions about age, gender, education and whether participants are already using smart home technologies (yes; no, but planning to get; no and not interested) were presented. The study ended with an open text field in case the participants had any comments or difficulties regarding the study.

*Sample.* 304 people completed the study. Data from one person was excluded because the answers were implausible (age 100, highest possible rating for each point); therefore information from 303 participants could be taken into account. 30% stated their gender as female, 68% male and 2% diverse. The age of the participants ranged from 17 to 81 years (M = 40.5, MD = 37, SD = 14.25). 49% already used smart home technologies, 19% stated that they did not own any but had planned to buy some. 32% said they did not have any and were not interested in them either. Splitting the sample into 4 age groups with equal ranges, the percentage of smart home owners was the highest in the middle-aged groups, while people below 34 or above 65 years of age were less likely to own a smart home ($\chi^2 = 23$, $p < .001$); $V = 0.17$, 99% CI [0.06, 0.29]), as we expected it for the older participants. The negative relation between technical affinity and age that we expected, as reported by the authors of the TA-EG [22], could not be confirmed in our study (p > .01).

## 3.2 Results

Positive attitude towards technology was positively correlated (Spearman) with positive ratings in all UEQ scales of both approaches ($\rho$ between .30 and .38, $p$ < .01) while negative attitude was correlated negatively ($\rho$ between -.24 and -.30, $p$ < .01).

Both the SL and the RL approach got positive mean ratings between 4.34 (Attraction, first approach) and 5.39 (Perspicuity, second approach) on every UEQ scale. The UEQ Handbook gives a "standard interpretation", which says that values >0.8 above the medium score represent a positive evaluation [47]. This was the case for the Efficiency and Perspicuity scale on both approaches (SL: M = 4.92, M = 5.36 RL: M = 4.96, M = 5.39 on a scale from 1 to 7). In addition, a one sample t-test showed that all ratings were significantly different from the medium score. The effect was high on the Perspicuity scale (Cohen's d = 1.04; d = 1.00), middle on the Efficiency scale (d = 0.75; d = 0.71) and small on the others (d between 0.25 and 0.40). Because ordinal scaling of our own items has to be assumed, the t-test is not applicable here. Rather high mean ratings were found for understandability (M = 4.15, M = 4.22 on a 5 point Likert scale), mean ratings between M = 3.55 and M = 3.86 for the other positive items and lower ones (M = 2.46, M = 2.55) for the negative item. As mentioned above, these items were correlated with the UEQ scales. Comparing the two approaches, paired t-tests showed the reinforcement learning approach was rated higher with mild significance on the UEQ scale stimulation (SL: M = 4.34; RL: M = 4.48; t(302) = -2.56, $p$ = .011, -0.03 [99% CI -0.19, 0.12], d = 0.10). A Wilcoxon signed-rank test for matched pairs showed to our surprise it was also perceived as more controllable with high significance (SL: M = 3.66; RL: M = 3.86; V = 2398, $p$ < .001; 99% CI [-9.9994e-01, -6.7536e-05], $r$ = -0.20). We used the Wilcoxon test because ordinal scaling of the question has to be assumed for our own Likert scale items (while the UEQ items are supposed to be metric). For people who already owned smart home technology or did not want to, these effects were not significant. However, in people who were interested in getting a smart home, in addition to the correlations with stimulation and controllability, there was a significantly higher score on Efficiency (SL: M = 4.97; RL: M = 5.32; t(57) = 2.77, $p$ < .01; 99% CI [-0.68, -0.01], d = 0.32), in accordance with our assumptions.

## 3.3 Discussion

Our results indicate a potential for user involvement in the learning phase of a smart home. We gained initial insights into how users perceive providing labels for activity recognition and how this affects their feeling of control over a system. Furthermore, we gained insights into users' perception of supervised and reinforcement learning in a human-like interaction and how this might affect users' understanding of the technology.

We were surprised that the RL approach was perceived to be even more controllable than the other one. We thought it would be clearer in the SL approach for participants how the given information can be used by the smart home agent, in contrast to the RL approach where there is no insight how the algorithm interprets the Boolean-like input. Nevertheless, our results show support for both approaches.

In our further research, we wanted to focus on both approaches separately in more detail. As our next step, we decided to further investigate users' perception of participation in supervised learning for activity recognition because the RL approach is most likely to follow the SL: First, basic skills are taught through SL, then refinement is done through RL. To overcome the limitations of online studies and provide a more realistic experience, we conducted a laboratory study using a prototype and a Wizard of Oz methodology.

# 4 MAIN STUDY

In this study, we gave users the opportunity to actively experience training a smart home agent based on activity recognition. We have developed a prototype of an app that can inform a smart home when a certain activity is started and when it is ended. This way, an envisaged SL algorithm is supposed to be provided labels that can be attributed to the smart home's sensory information. On the start screen, designed in a simple and appealing way, users can select an activity they want to start from a list. After selecting an activity, a screen shows the current activity, the time since it was started and a button to declare the activity ended, which then leads back to the start screen. The prototype used in the study did not send the labels to the smart home but recorded when which button in the app was pressed, so the authors could easily monitor how the participants used the app during the experiment.

## 4.1 Method

We conducted a laboratory study in a prototypical smart home apartment. The apartment consisted of one room with living room furniture, bed, work desk and kitchen. Participants were recruited via public online groups with local references (e.g. "classified ads Duisburg"), postings in public places in the neighbourhood of the laboratory (e.g. diners) and word-of-mouth recommendations. For participation, which lasted 1–1.5 hours, they were compensated with 20€.

Participants were welcomed by the experimenter, led into the smart home and briefly informed that the goal of the study was to test a new approach to teach a smart home how to recognize activities of residents in the home. After signing the privacy statement, participants were given one page describing what a smart home is and what activity recognition in a smart home can be used for, but not given any information on how the smart home agent is able to do this or how the learning takes place. Participants were asked if they had further questions and then given the first questionnaire. In this, they were asked for sociodemographic information about age, gender, education and occupation, and their agreement to six statements (see repository at https://osf.io/gft4e) on a scale of 1 to 7. The statements addressed their perceived understanding of AI (one positive and one inverted, negative statement), controllability and usefulness of AI, and perceived control and privacy risk of smart homes. These statement items were held abstract and general and were asked again after the smart home training procedure to measure implicit effects of the training on general perceptions of AI.

After completing the first questionnaire, they were instructed how to "teach" the smart home to recognize their activities. Participants were shown the app and informed how it is used. They were told that for this study, they should choose 3 of 6 possible activities to do in the apartment: Watching TV, reading, preparing tea, preparing a meal, eating a meal and doing fitness exercises. They were instructed to behave naturally, as they would do these activities in their own home, and to inform the smart home via the app when they started or finished each activity. Participants were briefly explained that the smart home would connect the information on which activity is being executed with sensory data of motion sensors and smart devices in the home. This way, it would later be able to tell from similar sensory information which activity is executed by the resident. In fact, our prototype did not yet actually collect any sensory information. Instead, we had fake motion sensors installed in the apartment to make the prototypical smart home look fully realistic. They were also informed that the cameras were not part of the smart home concept and were only used for the experimenter to be able to monitor the participants during the experiment. The experimenter left the room and waited for the participants to complete their chosen 3 activities while using the app to "inform" the smart home about it.

After each participant was finished, the intended effect of the training was demonstrated using a Wizard of Oz approach: Participants were told that although the training was not yet complete, the smart home had now gained a low ability to roughly recognize the activities presented. As a simple example, the experimenter would now program the smart home to switch on the light when the participant executes a specific activity A that they performed during the experiment. The participant was then asked to put the app away and start executing activity A again. When the participant did so, the experimenter switched on the smart lights. This way, the participants should get a brief impression of the effect of the training approach tested in the study.

Participants were then asked to complete Questionnaires 2 and 3. Questionnaire 2 asked participants to rate their experience with the process of teaching a smart home how to recognize their activities using the short version of the UEQ. Five additional rating statements addressed their understanding of how the artificial intelligence in this smart home worked, perceived controllability, control over privacy and privacy risk (inverted, negative statement) of this smart home, and their understanding of how the smart home learns to recognize activities. While the focus of our paper is on perceived understanding and control, we added privacy questions as a possible side influence, as privacy concerns are a common issue in smart home systems that can also affect acceptance [7, 11, 27, 59]. Questionnaire 3 contained the same questions as Questionnaire 1.

After completing the questionnaires, the experimenter conducted a qualitative, semi-structured, guideline-based interview. The interviewer asked the participants (1) if they had any further questions or comments; (2) if they already used any smart home technology and if yes, which; (3) if the participants had understood what they had to do during the experiment; (4) how they liked the process and if they perceived it as rather easy or complicated. Participants were then asked (5) how much effort they would consider appropriate from their personal perspective to train a smart home to have (a) comfort functions, (b) energy saving functions, or (c) ambient assisted living (AAL) functions. Regarding ambient assisted living, they were instructed to imagine doing this for an older relative whom they had to help install the smart home system. Participants were then asked (6) their general opinion of this smart-home training concept and (7) whether they felt they had a better or worse understanding after the study procedure, i.e., they felt more confused about how AI works and why. Finally, a smart home system was described to them that learns by itself without their participation (i.e., an unsupervised learning system) and asked to compare this to the system that they were presented in the study. Thus, they were interviewed on possible advantages they felt or imagined (8) the unsupervised system and (9) the presented supervised system had. Finally, participants were asked about their thoughts on privacy regarding (10) smart home systems in general and (11) if there were any differences specifically regarding the presented system.

**Table 1: Answers to first questionaire before and after the main study in terms of their test statistics of the Wilcoxon signed-rank test (mean, Z-score, p-value, effect size r).**

| Question | M(pre) | M(post) | Z | p | r |
|---|---|---|---|---|---|
| AI Understanding | 4.33 | 5.20 | 2.84 | <.01 | .52 |
| AI Understanding (neg.) | 3.57 | 3.27 | 0.95 | .34 | |
| AI Controllability | 4.67 | 5.33 | 3.01 | <.01 | .55 |
| AI Usefulness | 6.40 | 6.70 | 2.64 | <.01 | .48 |
| SH Controllability | 5.57 | 5.60 | 0.25 | .80 | |
| SH Privacy Risk | 4.13 | 3.70 | 2.34 | .02 | .43 |

After the interview, participants were debriefed about the prototypical nature of the smart home and the Wizard of Oz procedure, thanked and handed their compensation.

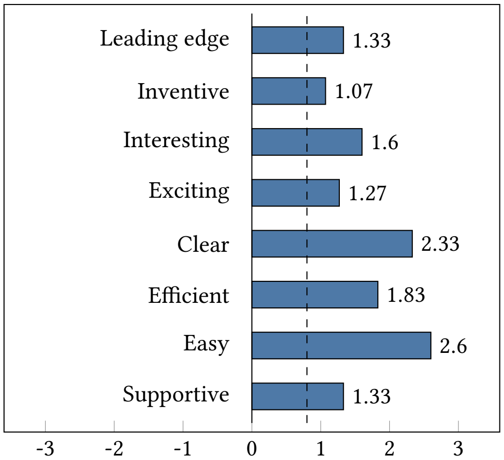
*Sample.* 30 people from Germany took part in the study. 14 (47%) stated their gender as female, 16 (53%) male and 0 diverse. The age of the participants ranged from 18 to 63 years (M = 32.4, MD = 26.5, SD = 13.5). As their highest educational degree, 33.3% had a university degree, 20% an official German professional training, 40% a higher education entrance qualification and 6.7% a secondary school certificate. 53% were employed, 36% were university students from different fields, 1 was job-seeking and 1 did not want to answer this question. Of the employed participants, 2 were software developers; all others had jobs that had no discernible relation to the topic of our study. Of the 8 students who reported their field of study, 1 studied mechanical engineering; the others studied subjects unrelated to our topic. 12 participants (40%) already used smart home technology at home (interview question 2). This was mostly voice assistant technology, Smart TVs or simple tools like smart lights or sockets. One participant had a more complex solar system and heat pump in their house.

## 4.2 Results

In the following section, we present the results of our questionnaires and interviews. Interpretation and implications follow in Section 4.3.

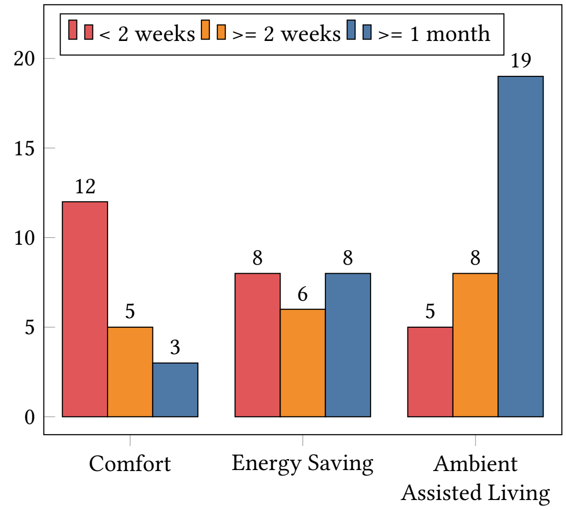
*Questionnaires.* The results for the pre-post questions are presented in Table 1. For the pre-post comparisons of our custom items, we used the Wilcoxon signed-rank test for matched pairs. We found that after the study procedure, participants gave significantly higher ratings on their understanding of the functioning of AI, perceived controllability of AI and usefulness of AI. Furthermore, they saw smart homes slightly significantly less as a risk for privacy. For

**Figure 1: User Experience Questionaire (UEQ) mean ratings of the smart home system after the main study procedure.**




Values >0.8 represent a positive evaluation.

**Figure 2: Users' willingness to invest time in AI training: frequency of responses per smart home category.**




the inverse item about participants' understanding of AI decisions and the item about smart homes being controllable for their users, pre-post differences did not get significant, though they were in the expected directions. For detailed results, see Table 1

Regarding the UEQ, according to the handbook, with possibles scores ranging from -3 to 3, values >0.8 represent a positive evaluation. Our participants rated the experienced procedure to teach the smart home 2.0 on pragmatic quality and 1.3 on hedonic quality. See Figure 1 for detailed results.

For our custom items regarding the presented "smart home", we used the one-sample Wilcoxon signed-rank test to test for deviation from zero. It was highly significant for understanding of the smart home's AI (M = 5.63, $z$ = 4.43, $p$ < .001; $r$ = 0.81), understanding how the smart home learns (M = 5.77, $z$ = 4.31, $p$ < .001; $r$ = 0.79) and perceived controllability for its users (M = 5.9, $z$ = 4.61, $p$ < .001; $r$ = 0.84). Controllability of privacy was also rated significantly above zero (M = 4.87, $z$ = 2.67, $p$ < .01; $r$ = 0.48). Privacy risk (negative item) was rated slightly significantly below zero (M = 3.43, $z$ = 2.04, $p$ < .05; $r$ = 0.37).

*Interviews.* We transcribed the interviews. Then, for each question, we formed categories from repeated or synonymous keywords and assigned each answer to one or multiple categories. Unique or salient answers were noted separately. This way, we can quantify insights from the data and qualitatively interpret context, relations and reasons for different aspects mentioned by participants.

1. Comments: Participants had no noticeable questions or remarks regarding the questionnaires.

2. Smart Home technology usage: Results of question 2 are presented in the section "sample".

3. Understanding of experimental procedure: Answers to question 3 showed that participants had roughly understood the study procedure and their answers to the questionnaire were therefore reliable, even though participants' competence in describing the procedure differed. They often did not distinguish whether a smart home learns to recognize activities or associates activities with actions (e.g. the light should be turned on when the resident is reading). The assumption that the smart home agent will immediately learn to make these associations could be due to the fact that much of the existing smart technology is based on learning routines.

4. Liking of the training procedure: Participants perceived the training procedure as easy. Only three thought that doing this procedure at home might be complex. A greater share of participants described the procedure as pleasant, exciting or interesting or positively mentioned the fact that they only had to do things that they would do anyway and using the app was no real additional effort.

5. Time investment to train smart home: For each of the three functions (1. Comfort, 2. Energy Saving, and 3. AAL), we talked to participants in detail about what they considered an appropriate amount of time (minutes/hours per day over how many days/weeks/months) to train the AI system. First, participants' answers ranged from a few minutes to a whole year. Second, the times stated within-participant heavily depended on the type of functionality. For comfort functions, many were not willing to invest a lot of time because they did not perceive them as useful or necessary. Energy saving functions, in contrast, were considered more important by most participants, who were therefore willing to invest more time. Strikingly, nearly all participants stated they were willing to train AAL systems for a much longer period of time since they perceived these as much more important and useful than the others. Sometimes participants gave only vague answers or comparisons (e.g. that they would invest more time for energy saving than for comfort function, but not how long exactly). The following analyses reference the answers providing concrete time frames. Since most answers were given in the first manner and in a range of a few days or weeks, we formed three categories to assort time frames x provided in the answers: x < 2 Weeks, 2 weeks <= x < 1 month, x >= 1 month. Results are presented in Figure 2.

6. Opinion about training concept: Reactions and opinions about

the presented training methodology were quite similar. Participants perceived it as easy, useful and innovative. Some participants mentioned various aspects that were also discussed in more detail in the responses to other questions, such as time required for installation or personalization.

7. Increasement of understanding: The majority of participants (60%) reported after the procedure that they had a better understanding of how AI works, supporting the results of the implicit data from the questionnaire. Six participants attributed this directly to participation; five also mentioned the experimenter's explanations or seeing how the smart house works (the Wizard of Oz); the others could not give a specific reason. No participant reported confusion or a feeling of less understanding after the procedure.

8.+9. (Dis)advantages of (un)supervised training: We wanted to reassess whether users would prefer an unsupervised system or a system supervised by them. To avoid biasing their answers, we asked them about the benefits of each system separately. As might be expected, participants saw the benefits of an unsupervised AI smart home system as requiring less effort, time, and knowledge from the user. However, more than a third of users expected a supervised system like the one presented to reach a higher degree of personalisation. Furthermore, five participants positively mentioned the possibility of deciding what to teach the system and what not, while one of them and three others explicitly mentioned having more "control", without the interviewer asking for it or having mentioned control in any way before. Only three participants could not think of any benefit of a supervised system.

10.+11. Privacy concerns: Finally, we were interested in participants' perceptions of privacy and if they perceived any differences regarding our system. 20 participants (66%) stated they had concerns regarding their privacy in smart homes. Reasons were mostly related to the data handled being very private and insecurity about how they are used by the providers. Nine participants stated they had fewer concerns with our presented smart home system, with the main reason being that the system does not use cameras or microphones. One participant responded that it was preferable to operate the system by herself, while another mentioned having more control over what the system learns.

## 4.3 Discussion

We found strong support for our hypothesized benefits of involving users in AI training. We found that after our user-supervised AI training procedure, participants reported an increased feeling of understanding of AI, perceived AI as more controllable and thought of AI as more useful. Especially the high effect size for perceived controllability was remarkable. Of course, the generalizability of our hypothetical smart home agent is low, but we can see that the exemplary interaction with a specific AI device influences the general perceptions of AI. These implicit measurements regarding understanding and perceived control are supported by the explicit qualitative data from the interviews.

Interestingly, for perceived controllability of smart homes, the difference did not reach significance. From what we learned in the interviews, this is because there are more factors to the controllability of a smart home than just its AI and these can be critical to users. Multiple users asked about how the smart home could be controlled after it learned to recognize the activities, or about a feedback system / interface to get information on the smart home's activities. The interview questions about privacy also revealed many control-related concerns regarding data storage and usage. All of these issues might impact participants' sense of control over smart home systems regardless of the control over the AI, which could explain the insignificance. Nevertheless, our participants saw smart homes as less of a privacy risk after the procedure. We attribute this to the smart home system proposed in our study, which serves as a positive example. However, as mentioned earlier, opinions on privacy seemed to be strongly influenced by factors irrelevant to our research question, such as the presence of cameras, so we would suggest interpreting this part of the results with caution.

The goal of our study was to explore the general chances of user participation in the training of intelligent agents in the smart home use case and not to propose a concrete smart home system; therefore, we do not discuss the possible implications for the design of smart home interfaces and hardware components.

*4.3.1 Users' willingness to participate in AI training.* Regarding the willingness of users to engage in the training of an intelligent agent in a smart home, results are positive. The training time frames for each function that participants considered reasonable were often high. While the smaller time frames for comfort functions were likely due to participants' general lack of interest in these functions, time frames for training an AAL system for an older relative were sometimes exceptionally high, even though the participants would not benefit from the technology personally. Some participants stated that they had no upper time limit for this purpose. In addition to often being willing to invest time in training, many users saw and valued the potential benefits of a supervised system. For more than a third of participants, the presumed benefit was better functioning, mostly in the form of higher personalization; for about another third, it was control-related reasons, e.g., the ability to decide what should be learned by the AI and what not. Existing studies could already show that older people have a high interest and positive attitudes towards smart home technology, including sensors for assistive purposes [14, 15], which could be realized with the help of relatives or caregivers. In conclusion, we assume that if a user is interested in a particular smart home function, the need to train an AI need not be a barrier to adoption. On the contrary, some users may even prefer this option to gain better functionality or control over their smart home.

# 5 GENERAL DISCUSSION

In our studies, we gained insight into users' perception of being involved in the supervised learning of an AI system. We found that users are open to this possibility and have mostly positive feelings about it. Though the human-AI interface we used in our study was only a simple prototype and not very sophisticated, as design details were not our focus, participants already gave high user experience ratings and expressed that engaging in the AI training felt easy and could be integrated in their everyday life without much effort. Future work could look more into the design of such interfaces.

After participating in the learning phase of an AI, our participants felt they had a better understanding of how AI works, thought of AI as more controllable and were more likely to think that useful application areas exist. The fact that the question of controllability was significant for an AI but not for smart homes makes it even more clear that users' perception of AI, in general, was changed and not just of smart homes as one application area. This result implies two important findings: (1) Users' perceptions of the general concept of AI can be predominantly shaped by a single "prototypical" AI system. (2) Actual acquired knowledge or control over AI does not have to be high to have a significant impact on general subjective perceptions of AI. In our study, users did not learn many details about how the AI works, and their control was limited to data input. However, participation in the training improved the attitude towards AI with remarkable effect sizes. This may be useful for providing users with a better user experience and control in an ethical and explainable AI system; however, it may also be misused to deceive users into trusting a questionable black-box AI. It must be emphasized that in this study we intentionally focus on users' perception of understanding. While XAI approaches mostly rely on providing information to users, our goal was to focus on their processing of this information. For users' wellbeing, it is not only important that they receive information but also that they develop a sense of deeper understanding. Certainly, to ensure users' control over the smart home technology, objective understanding is also required. In this context, it is a valuable finding that users consider the information they gain from participating in the training process as relevant to their understanding of AI.

Regarding the different phases from the construction of an algorithm to its application, our procedure focused on data input. Although this is the step in which users are most involved (albeit possibly in a passive way) because the agent must learn from their individual behaviour, research has so far neglected to investigate the user experience of this process. We have raised the question of the importance of input data in the pursuit of intelligent agents that users perceive as understandable and controllable.

Finally, one can question the assumption that users would be too unmotivated to invest work into a smart home system with supervised learning [57]. Instead, some users might even appreciate the opportunity to gain control over their input data. This need not be an obligation, as a system could use a combination of unsupervised and supervised learning. As in our study, such training could easily be implemented with a simple labeling app, and we would like to encourage developers of smart home systems to try the implementation of such a user interface.

Our work is limited to a specific phase in the implementation of a specific type of AI. We explored the possibility of involving the user in AI training to lay the groundwork for the future development of concrete smart home agents or similar AI systems. In future work, we could now design a more detailed concept for a smart home with training capabilities for the user to test the transferability of the results of our Wizard of Oz approach to a real-world application. The same applies to the complexity of the task and the time actually required to train the system. In the interviews, participants only provided estimates of how much time they would be willing to spend on training. Also, with regard to the preliminary study conducted online, the participants' estimates are not based on their experiences in a real AI-supported smart home. Here, further studies, especially long-term studies, could provide insightful findings and further developments of our considerations.

A next step could be the development of a concrete smart home system in collaboration with industry partners, followed by a field study. In this setting, users' willingness to train AI for a long period could be tested, and both perceived and objective understanding as well as their correlation could be measured, which would be a psychologically interesting question. Moreover, the interaction of different aspects of understanding and user experience identified in this and previous work could be examined. For example, our smart home training approach could be combined with a self-explanatory XAI system [25] to make the algorithm even more transparent and provide additional intervention options [20, 29, 46].

We see our work on increasing perceived understanding and control embedded in the process of developing AI technology.

(1) Design phase: Methods of user involvement from the very beginning to take into account user needs and requirements.
(2) Training phase (this work): User participation in data collection and training, creating greater subjective transparency about what private user data is used for what purposes.
(3) Understanding during usage: XAI methods for explaining AI decisions to bring objective transparency into the algorithm's reasoning and decision-making.
(4) Control during usage: Measures for readjustment of the algorithm by the users, such as reinforcement interfaces (as explored in our pre-study) or intervention user interfaces.

Taking these approaches together, we can provide users agency and improve their understanding and personal sense of the latter two aspects, thus creating ethical AI applications.

## 6 CONCLUSION

We found that involving users in the training of AI enhanced their feeling of control, perceived understanding and perceived usefulness of AI in general. Participants reported a high willingness to train an AI to gain smart home functionalities for themselves or their relatives and found the process understandable and controllable. Involving users in the learning phase could therefore lead to a better personalisation and user experience. Our study complements recent efforts to empower users and improve their wellbeing through understanding and control.

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