Automated Decision Making Systems in Smart Homes: A Study on User Engagement and Design

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Abstract

Automated decision making (ADM) systems are in the center of smart home technologies. With the recent advancements within the fields of artificial intelligence (AI) and internet of things (IoT), ADM systems are becoming increasingly smart and arguably more comfortable and accurate in their automated decision making. However, there are still questions regarding the design of human-machine collaboration in the home. How exactly do users engage with smart technologies in their homes? How do they maintain control over their systems when something does not work as expected, and how can we design for co-performance between users and AI? Our research investigates such questions in the area of user engagement in automated decision making (ADM) systems in smart homes. In this paper, we outline first findings and perspectives from an ongoing literature study on this topic, which we intend to investigate further in our future work.

Keywords

smart home, decision making system, home automation, user engagement, human-centered AI

1. Introduction

"Looking through history, we saw the enlightenment of sages, who think that one day machines can do most of the things in replace of humans, free of your mind, free of your hands, no thinking, no action, all the best is prepared for you."

Automated decision making (ADM) systems are improving thanks to the rapid development of artificial intelligence (AI) and internet of things (IoT) technologies. Smart homes with automated decision making systems promise to make homes smarter, more intelligent, and energy-efficient at the same time. The definition of smart home comes from Intertek in September 2003. More specifically according to their DTI Smart Homes Project: a smart home is "a dwelling incorporating a communications network that connects the key electrical appliances and services, and allows them to be remotely controlled, monitored or accessed" [1]. ADM systems are one of the key components of smart home automation that make use of the sensor data, and exploit different kinds of algorithms to analyze them and perform actions on behalf of the inhabitants. Smart homes have been studied from various perspectives, ranging from more technology-oriented studies about IoT sensor networks and actuators to algorithmic decision making and the use of AI for better results [2]. For example, Hemant Ghayvat's work

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exposed the complexity and data delay of sensor networks and proposes a new Wellness Sensor Network which is used for assisted living in smart homes [3]. John Jaihar's work introduced a novel smart home automation system based on different machine learning algorithms and computer vision. They proposed AI system that can collect users' emotions to provide better automated decisions[4]. Hussain Kazmi's work illustrated strategies of automated decision making algorithms in smart homes and exposed the potential function of these algorithms [5]. Other streams of research have looked into how users interact with smart systems, and how they interpret the data in terms of "data work". Castelli et al. developed a flexible dashboard system with configurable pre-defined widgets and an end-user development (EUD) environment to solve individual data-related demands in smart homes [6]. In particular, some streams of studies are interested in designing human-machine collaboration not as automation but as form of co-performance. Based on the concept of co-performance from Lenneke and Elisa's work [7], Lawo et al. presented a case study on a personalized food recommender systems [8]. Such approaches might be interesting because they provide users control over automated decisions, and enhance transparency as well as the comfort in the interaction with ADM system.

Working towards this topic, we are interested to study how users engage with ADMs in their smart homes. How do users set up and interact with their smart home technologies, how do they respond to potential unwanted behaviors or fine-tune the systems to their individual and situated needs? By better understanding these practices, we hope to inform the design of ADM systems that allow co-performance between users and AI. This is especially important for the question on how to design ADM systems that are able to deal with conflicts of interests, such as how to navigate the fields of tension between automation and being in control, as well as between the need to preserve energy and provide comfortable living environments.

In this position paper, we outline the first stage of our research idea as a brief literature review on algorithmic decision making in the smart home, and discuss in which areas we see potentials for designing for co-performance between ADM systems and their users in different scenarios.

2. Understanding Users

There are at least three roles to consider in the design of automated decision-making systems: the designers, the users, and the affected persons. Designers are the ones who devise the automated decision-making systems [9]. They think of all of the factors that will have an influence on the desired results and calculate the weights of these factors. They search for a suitable algorithm (or a combination of algorithms) compatible to perform with different kinds of decision making scenarios. Users are the ones who are directly involved in the operation of the ADMs. For example, in the smart home environment, user might be someone who sets up the system, defines schedules for heating or sets rules for automated actions that the system should take based on certain events. Even when a system is strongly based on algorithmic decisions, users can often overrule or fine tune those to their individual needs. The affected persons are also users, but those are rather passively exposed to their automated decision-making.

Understanding different kinds of roles involved in designing automated decision-making systems is very crucial. It solidifies the foundation of designing human-centered automated decision-making systems. For instance, designers usually have a good understanding of the technological basis, but need to learn about the needs of users in order to build systems that are successful in practice, calling for user-centered design processes [10]. Users, on the other hand, should not only be those who are the operators of said systems, but also persons who are affected by the decisions that are taken.

In this position paper, we focus on the users as both the persons who interact with the automated decision-making system or are exposed to their decisions. We try to understand their needs based on different smart home application areas, analysing what problems might exist in the interaction and how to design a well-fit automated decision-making system in smart home that allows co-performance between AI and users. By doing so, we intend to put the human in the loop of ADM systems.

3. Application Areas of ADM systems in the Smart Home

In the first phase, we investigate the application areas of ADM systems in smart homes. Based on a literature review, we identified several areas where ADM systems play a role. In this position paper, we only focus on three areas - eHealthcare, energy management, and entertainment. While we can foresee that there will be more "playgrounds" for ADM systems in smart homes in the near future, these are currently the most prominent application areas.

3.1. eHealthcare

With the increased cost of healthcare of aging societies and the development of IoT, eHealthcare has become a major service that smart homes can provide. The concept of Ambient Assisted Living (AAL) has become a major research topic in the last decades [11]. Combining healthcare systems with smart homes can provide elderly users with "high quality, low cost and easily accessible" care [12]. This is provided by ADM systems based on different kinds of sensors [13] that collect safety-related data about the environment as well as the users' health situation.

This data is then analysed by automated decision making systems to provide diagnostic information, call help when needed, or provide health monitoring data for physicians.

ADM systems in eHealthcare so far usually provide little means for user engagement [14]. They are often setup by experts and provide largely passive functions such as disease diagnosis [15], emergency notification [16] and health monitoring [17] for the user, but without much means for user control. However, health situations of elderly people can be very diverse, and there is a huge potential in giving users more control over their ADM systems in order to address sensitive issues (such as privacy related to health data or interaction with potentially distressing diagnosis decisions), as well as allowing for more fine-tuned and situational support in complex situations (i.e., disease recovery).

Due to the low level of user control, there exists potential room to think towards higher user engagement, providing more interactive interface and making decisions more transparent. In turn, these will increase users' trust and allow for more complex interactions with automated decisions[18]. However, there are also challenges due to the safety-critical aspect of those systems, that call for special support approaches and careful considerations.

3.2. Energy Management

For energy management, ADM systems are used to minimize the cost of energy consumption and maximize the comfort of inhabitants. This can happen on two levels: the first level refers to automated decisions based on the smart grid (e.g. starting appliances automatically when there is a low energy demand on the overall grid). The second level is based on sensor information from the smart home energy management itself (i.e. lower the heating when no user is present at home).

Data are also exchanged between these two levels, to identify behaviour patterns for grid optimization. Due to the challenges of the climate crisis, energy saving is often in the focus of such systems, though they also provide comfort to the users in terms of automating things that have previously been needed to be done manually (such as turning off thermostats when leaving the house)[19].

In energy management, ADM systems usually offer a rather high level of user engagement, allowing (or requiring) to set up complex rules and time schedules for the operation of the smart home. This is required because the energy demand is usually varied person to person, and living situations will change over time. Furthermore, a lot of the energy demand is strongly related to the user behavior. Therefore, approaches such as providing eco-feedback, gamification and nudging are commonly considered here. As smart grid based automation (such as starting the dryer at night when energy is cheap) might interfere with individual living situations and requires user engagement, those systems will usually provide different usage scenarios for users to select (i.e., optimizing for comfort, saving energy, or security)[20].

While Energy Management offers a high level of user engagement, we see a high potential for designing for co-performance due to the inherent fields of tension between energy saving and user comfort. Finding the sweet spot between different aims is difficult, and also a system which requires a high level of user engagement and interaction can be more challenging to set up(if it provides high levels of control) or rids of the user of control (in case of full automation). This especially affect users that live with these systems and are affected by them, but don't operated the systems themselves.

3.3. Entertainment

Another area of ADM systems in the smart homes is related to entertainment and digital consumption. Here, automated decisions mostly refer not only to the recommendation of digital media (such as music streaming to smart speakers or movies on smart TVs), but also to other comfort functions such as providing easy access to the Internet based on voice interaction with smart Voice Assistants such as Amazon's Alexa, Google Assistant or Apple's Siri [21]. These ADM systems perform based on analysis the user preferences about digital media, as well as patterns that are detected in the preferences of the overall user base of the service providers (such as 'customers who liked this, also liked that'). Having good recommendation mechanisms has turned out as a major competitive advantage of the digital economy (next to having control over platforms themselves) [22].

In the area of entertainment, users are passively engaged in the system. The level of user engagement is low. Users can provide feedback to the systems by "disliking" media or marking automated suggestions as "irrelevant", but there does not exist ways to control the system besides that.

It seems that users are engaged in the systems all the time, but ADM systems remain transparent in the background and users don't interact with the ADMs directly. Decisions in this area are highly related to the concept of taste [22], which can be a highly complex phenomenon. Under the such situation, we see a potential opportunity for future designs in it, especially involving the voice assistant into it. In terms of interaction with Voice Assistants, there is also a lot of potential for designing for a better co-performance using Voice Assistant. We can make a reference to other ADMs application areas with voice assistant[23], which has already established in practice and provide a lot of functionality in terms of user interaction and feedback.

4. Design Challenges and Future Work

In our study we have found different levels of user engagement and automation at smart homes across the different domains. As we have outlined, there are a lot of open issues to be solved, and also a lot of research opportunities in the different areas, which are often also entangled in practice–smart homes intend to provide safety, comfort, entertainment, and also means to preserve energy at the same time. Due to the high variance of individual needs, life situations, and the high complexity of the problem areas, we agree with the concern that there will be no fully automated solution in the sense of a "one-size-fits-all" approach, but we will need to consider the human in the loop for automated decision making [24].

In our future work, we would like to study the different domains in more detail, understanding how users appropriate such systems in practice, how they interact with each other, and how we can improve those interactions in terms of giving users more control without compromising on their comfort of living. This will not only require to make systems more transparent in terms of their decision making [25], but also to provide the means to users to co-perform with their home ADM systems. Hence, this will provide them the power and means to adapt a system to their individual needs and living situations without giving up their aim to preserve energy and contribute to the combat against the ongoing climate crisis. By studying touch points, interfaces, practices and fields of tensions between competing interests, we hope to inform the design of more adaptable ADM systems, support appropriation and empowerment of users of such systems in various domains.

In doing so, we intend to experiment with different forms of interfaces, provide different entrances to the ADM system configuration that are also suitable for less engaged-users. This will provide them a feeling that they are living with ADM systems but (so far) have not actively engaged with them. We would like calling for "smart assistants" that provide a high level of control but also good usability and appropriation support for the users that engage with them [26]. Our assumption here is that as individual personal assistants (IPAs) already provide a very low level entrance to ADM systems, it can also be exploited to provide users with higher levels of control. Therefore, we assume that IPA can be used as bridge to connect the human and machine in terms of supporting ADM appropriation and control, which we want to study further in our future work.

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