HHAI 2023: Augmenting Human Intellect
P. Lukowicz et al. (Eds.)

doi:10.3233/FAIA230076

# Review on the Application Areas of Decision-Making Algorithms in Smart Homes

Lu JIN [a,1], Alexander BODEN [a]
[a] *Fraunhofer-Institute for Applied Information Technology FIT, Germany*
ORCiD ID: Lu Jin https://orcid.org/0000-0001-6901-4580, Alexander Boden
https://orcid.org/0000-0002-6470-1151

**Abstract.** Automated decision-making is one of the fundamental functions of smart home technologies. With the increasing availability of Artificial Intelligence (AI) and Internet of Things (IoT) technologies, those functions are becoming increasingly sophisticated. While many studies have been conducted on optimizing algorithms to improve the accuracy of predictions, less attention has been paid to how humans interact with algorithmic systems. This involves questions such as to what degree humans are involved in the algorithmic decision-making process and how we can design meaningful interactions between humans and systems relying on decision-making algorithms. With these questions in mind, our paper presents a literature review on the current state of decision-making algorithms in smart homes. Based on an analysis of 49 selected papers, we present a systematic investigation towards the application areas and the deployment functions that decision-making algorithms currently take in smart homes. Focusing on two main application areas – energy management and healthcare, our paper sheds light on the current deployment of decision-making algorithms in smart homes and identifies the current intentions of involving humans in-the-loop. Within the background of facilitating human-in-the-loop as an interaction paradigm, we aim to expose the design challenges for human-in-the-loop decision-making algorithms in smart homes which can pave the way for developing more effective human-machine hybrid intelligent systems in smart homes in the future.

**Keywords.**
smart home, decision-making algorithm, human-centered AI, human and algorithm interaction

## 1. Introduction

A smart home is an application area of ubiquitous computing in which the home environment is equipped with ambient sensors and actuators to provide context-aware services and facilitate remote home control [1], aiming to provide comfort, safety, and save energy for the inhabitants. With the rapid development of AI (Artificial Intelligence)

[1]Corresponding Author: Lu Jin, lu.jin@fit.fraunhofer.de

technology, smart homes are becoming more sophisticated. While early versions mostly depended on time tables and simple sensor readings, newer designs of smart homes analyze data with the help of machine learning technologies to detect patterns automatically and make more sophisticated decisions for their users. Even though users are still in control and can override automated decisions of their smart home systems, there is the question how such forms of human-algorithm interaction can be designed in a way that ensures both comfort and transparency. Our study seeks to understand the current state of decision-making algorithms in smart homes, investigating application areas as well as their deployment situation. Through a literature analysis of current works in the area of algorithmic decision-making in smart homes, we aim to achieve a bird-eye view and investigate design opportunities for human-algorithm interaction design.

We can note that lots of studies have focused on improving the quality of decision-making algorithms [2][3][4] or applying such technologies to broader application areas [5][6][7]. At the same time, there are few studies on how humans interact with decision-making algorithms, even though existing studies have investigated the impact of algorithm decisions on human decision making, exposing a need to involve humans into the automation to reduce biases of the systems [8]. Some research [9] has shown that we need to put humans in-the-loop to help algorithmic decision-making to overcome their limitations. It exposes the difficulties of designing for human and algorithm interaction in various fields of applications and their impacts on our everyday lives.

This paper seeks to provide a systematic review towards decision-making algorithms in smart homes, an area where such technologies are arguably very impactful on human life. It aims at investigating the possibilities and challenges for human and algorithm interaction. Specifically, in this paper, we want to investigate

- RQ1: What are the functions of decision-making algorithms in smart homes that are currently discussed in the literature?
- RQ2: What are the design challenges of human-in-the-loop decision-making algorithms in this context?

The contributions of this paper are the following:

- We provide a systematic literature review towards functions of decision-making algorithms in current smart home systems.
- Based on an analysis of the state-of-the-art, we expose design challenges for human-in-the-loop decision-making algorithms in smart homes.

After the introduction, section 2 introduces the related work on the core issues that we are investigating. Section 3 describes the methodology that was used in our literature review. Section 4 provides a comprehensive overview on application areas and functions that decision-making algorithms provide in smart homes (RQ1). Section 5 goes on to discuss challenges for human and algorithm interaction, and analyses design challenges for human-in-the-loop decision-making algorithms in smart homes (RQ2). The paper closes with a conclusion and outlook on future work.

## 2. Related Work

### 2.1. IoT in Smart Homes

Internet of Things (IoT) technologies are at the core of smart homes [10]. Generally, the IoT describes "physical objects (or groups of such objects) with embedded sensors, processing ability, software, and other technologies that connect and exchange data with other devices and systems over the Internet or other communications networks"[11]. Hence, the IoT [12] bridges the gap between the virtual world and the physical world. Based on IoT infrastructure such as networked sensors and actuators, users can control their house appliances with devices such as tablets, mobile phones or computers. It aims towards "Home Automation" where users can control all of the devices in the smart home with all of the appliances connected to each other. Among others, it aims to increase comfort, safety, and also provide means for saving energy for the inhabitants (e.g. allowing to check from afar if a window is open or the stove still turned on).Apart from manual control, Artificial Intelligence (AI) increasingly plays a role in the smart home, for example, Alexa – a smart voice assistant from Amazon – uses speech recognition and natural language processing technologies to allow users to control appliances with their voice. Other smart devices try to detect behavior patterns and provide automated control of appliances based on the user habits. For example, if all persons left the home, with AI technology, the heater, fan or any device can be turned off and the door locked automatically. Xiao[13] divides AI functions in smart homes into 6 categories – activity recognition, data processing, decision-making, image recognition, prediction-making and voice recognition. In our study, we are concerned with the issue of decision-making in the context of smart home technologies, which we will further explain in the following section.

### 2.2. Decision-making algorithms

The definition of an algorithm is "a process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer" [14]. Decision-making [15] is a process in which an agent, no matter if it is a physical entity like a human or a non-physical entity such as a decision-support system, acts based on data observed from the environment. With help of algorithms or machine learning, computers can take decisions based on such observations and also act on them with the help of actuators (such as turning the light or a heater on or off). Systems that take such decisions on behalf of users based on algorithms (be it human-designed or trained automatically) is what we understand as decision-making algorithms in our study. Decision-making algorithms or algorithmic decision-making [16] are widely used in different areas to take automated decisions or help humans in making decisions. For example, in autonomous cars, decision-making algorithms can be used to decide where to go next[17], or how to manage to go to the destinations in the most effective way[17]; in the financial sector, decision-making algorithms can be used to evaluate the financial risks[18] or help people invest their resources in a sustainable manner across their lifetime [19]. In the area of healthcare, decision-making algorithms can be used to support diagnoses of the doctors [20][21], or help patients to make a decision towards purchasing a specific healthcare product based on individual parameters [22]. Further examples include aerospace applications, where decision-making algorithms can help to prevent midair collisions between aircraft[23], or other safety-critical domains such as firefighting wildfires, where decision-making algorithms can support safety and efficiency of emergency response operations [24][25][26].

Decision-making algorithms also appear in smart home scenarios, where intelligent buildings increasingly take ever more sophisticated decisions, for example in the domain of energy management, balancing energy loads based on the status of the energy grid [27] or control heating/cooling based on predefined values [28] (sometimes set by the energy providers as a recent example from the USA showed).

## 3. Methodology

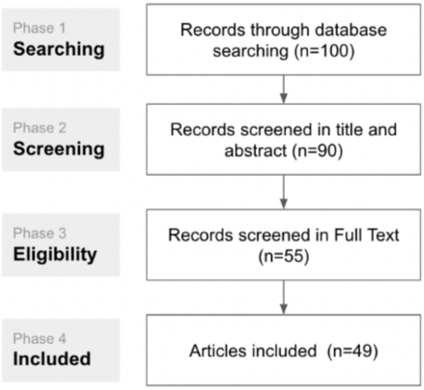


**Figure 1.** Procedural Visualization

### 3.1. Databases

Our literature review investigates the role of decision-making algorithms in smart homes. More specifically, we focus on the use of algorithms that automatically make decisions or support decision-making in the context of private homes. Relevant papers were identified by searching the scopus database. Scopus is the largest abstract and citation database which delivers a broad view on research from several fields, e.g. science, technology, social science.

### 3.2. Search Term

The search keywords have been “decision-making algorithms” and “smart home”. We tried other similar keywords, for example, “decision support tools” and “smart home”, “decision making” and “smart home”, but discarded papers that did not discuss algorithms as part of the system description. Moreover, because of the rapid development in the AI domain, and to narrow down our search to the latest research, we only collected matching papers from 2018 to 2022. Therefore, based on these criterion, in the first searching phase, 100 papers were selected.

### 3.3. Inclusion criteria

The title and abstracts of 100 papers were screened by the first author to identify whether they are related to our context – smart home and whether they discuss decision-making algorithms in an appropriate depth. Only full papers were considered for the analysis, leading to 10 papers being discarded. After reading the title and abstract, 55 papers where left for us to analyse deeper. Of these, we checked the full text in depth. In the end, we included 49 papers (see Appendix) in our analysis, after some had to be discarded by being too far of our research topic. For example, there were several papers that related to the smart grid, but did not cover the interaction with users [29].

## 4. Results

### 4.1. The Application Areas of decision-making algorithms in Smart Homes

RQ1 aims to identify the application areas of decision-making algorithms in smart homes. According to the literature review, there are two main application areas - energy management and healthcare. Among all of the 49 selected papers (see Appendix - Table 3), we found that 55% have contributed to the energy management application area, 16% have contributed to the healthcare area (see Figure 2). For other application areas, it includes entertainment, security and etc. In the following sections, we describe two main application areas in more detail.

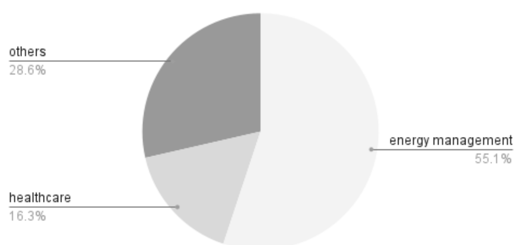


**Figure 2.** Application areas of decision-making algorithms in smart homes

#### 4.1.1. Energy management

In the smart home, one of the most prevalent application areas that decision-making algorithms apply to is energy management. Mostly, they are deployed as home energy management system (HEMS) to control and schedule home appliances. The main objective of the decision-making algorithms here is to minimize the cost of energy consumption and maximize the comfort of inhabitants in the smart home. Another objective is to make the smart home users "active in the energy market and reduce the pressure of the power grid including peak shaving, load shifting and etc and achieve better carbon efficient environment[30]". According to the literature review, energy management can be done both on the side of the smart grid and within the smart home. For the smart grid, it mainly focuses on optimising the supply side of the grid by involving users in the energy allocation decision making process. For the smart home, it mainly focuses on comfort and energy saving practices within the home, which can be related to smart grid technologies (but don't have to). For example, in the smart grid, the decision-making algorithms aim to allocate energy based on the (measured or predicted) user demands. Furthermore, applications within the home can be controlled from outside (with user' agreement) to improve the load balancing of the grid. Before the smart grid, the supply side management was only focusing on a single-side optimization problem, but with an energy management system (HEMS) installed in the smart home, the decision-maker in the supply side can get responses from the customers and have a "smart" interaction with the demand side. Current research is proceeding into the bi-level optimization problem with both the supply side and the demand side. Therefore, an iterative decision-making process between the upper-level optimization and the low-level optimization [31] is emerging. On the demand side in smart homes, energy management can "allow the end-users to communicate with the grid operator so that they can contribute in making decisions and assist the utilities to reduce the peak power demand through peak periods". For instance, Fanlin et al.[32] introduces a two-level decision-making framework between the smart grid and users. One level is for retails to announce their electricity prices for the next 24 hours, and the other level is for users to schedule their energy usage accordingly.

#### *4.1.2. Healthcare*

Healthcare in smart home or smart healthcare is the second major application area where decision-making algorithms are deployed in smart homes. The aim is usually to reduce the cost of healthcare and improve people's quality of life. Healthcare in smart homes is related to several special concepts such as "Ambient intelligence" or "Ambient assisted living" [33]. Ambient intelligence can be defined as "a computing paradigm that uses information technology and its applications to enhance user abilities and performance through interconnected systems that can sense, anticipate, adapt, predict, and respond to human behavior and needs" [33]. Ambient assisted living "aims at extending the time older people can live in their home environment by increasing their autonomy and assisting them in carrying out activities of daily living by the use of intelligent products and the provision of remote services including care services[34]". Decision-making algorithms are one of the fundamental functions in these concepts to help aging people in their daily life. There are several layers in smart ehealthcare homes [35] – sensors and actuators, home communication networks, autonomous computing as well as safety and healthcare services. Decision making is in the layer of autonomous computing, which handles the data from sensors and actuators in the inhabitant's environment as well as health data and takes decisions such as providing diagnoses, presenting reminders, or warnings etc.

### *4.2. The Functions of decision-making algorithms in Energy Management*

In this study, we focus on the two application areas which seem to be the most common use case (71%) in smart homes: Energy management (see Appendix - Table 4), and healthcare (see Appendix - Table 5). Based on the two application areas, we go forward to the detail functions that decision-making algorithms have in smart homes.

#### *4.2.1. Energy allocation*

We found one of the fundamental functions that decision-making algorithms have is for energy allocation between smart homes and the smart grid. Its main aim is to minimize the electrical consumption in the home, while still ensuring user comfort. For energy allocation between smart homes and the smart grid, the decision-making algorithms are deployed in the demand side management and consumer side management to distribute energy. Fanlin et al.[32] "proposed a two-level decision-making framework where the retailer acting as an upper-level agent firstly announces its electricity prices of next 24 hours and customers acting as lower-level agents subsequently schedule their energy usages accordingly." Through the feedback from the customers, an upper-level agent can allocate and distribute energy accordingly. Alisson et al.[36] "present a management system of residential loads based on the user's behavior, climatic variables and possibility of integration with distributed generation and Smart Grid. The system uses artificial intelligence (AI) techniques to make decisions on each automated load." Several types of data are used to make decisions, for example, "in temperature management, the resident's behavior through of the modification of parameters of air conditioners is used for temperature prediction" [37], and [38] introduce the cooperation and distribution between different smart homes and the smart grid in demand-side management to achieve optimized energy distribution. In [38], M. Hadi Amini et al. use distributed decision making from agents rather than central decision making on energy distribution.

#### *4.2.2. Energy consumption forecasting*

Forecasting is an another function that decision-making algorithms take. It is meant to support the energy allocation by providing better planning abilities for the energy suppliers. There are several methods used for decision-making in this area, for example, long short-term memory (LSTM) and fuzzy neural inference systems with genetic algorithms. In [39], they applied several pre-processing techniques to deal with the diverse nature of electricity data, followed by an efficient decision-making algorithm for short-term forecasting and implemented it over resource-constrained devices. Tao et al.[39] provide an efficient deep learning framework to predict the future energy consumption and also provide a communication between energy distributors and consumers. Accurate demand forecasting [40] is important for future strategic planning and scheduling. It can also help the consumers to minimize the cost of electricity.

#### *4.2.3. Home appliances scheduling and controlling*

Decision-making algorithms also provide functions for analyzing and making decisions for controlling and scheduling the appliances in the houses. Their main aim is to minimize the electrical consumption at home and reduce peak-to-average ratio while still ensuring user comfort. For example, Tengyue et al. [41] deployed decision-making algorithms to change the room temperature, which can adapt to the lifestyle of tenants and the outdoor temperature. Jordehi [42] introduced a new binary optimisation algorithm for optimal scheduling of appliances in smart homes. Bilal et al.[43] introduced a new EMS by scheduling the devices to minimize the electricity bills, alleviate peak-to-average ratio, and maximize user comfort. In this context, home appliances can be categorized into deferrable appliances and non-deferrable appliances. For example, dishwashers and washing machiness are deferrable appliances, while fridges are non-deferrable appliances. In some papers, the categories are named differently, such as shiftable appliances and non-shiftable appliances, or delay-sensitive appliances and delay-tolerant appliances [43]. Based on the differences in the appliances, the controlling and scheduling strategies are different. For example, Diego et al.[44] presented an optimization model to schedule deferrable appliances in households. They used two algorithm simulation-optimization approaches and a greedy heuristic for decision-making. The aim is to balance the electricity costs and user satisfaction.

#### *4.2.4. Anomaly detection / Device Management*

The decision-making algorithms also take over several minor functions, such as anomaly detection and device management. For anomaly detection, they use an algorithm to detect irregular patterns in activities and notify the relevant stakeholders. For example, [45] introduce a system that can forecast electricity bills and notify users if abnormal energy consumption of individual home appliances is detected. For device management, in [12] introduce the common machine learning algorithm – Support Vector Machine – to classify and handle the the status of devices. Zelin et al.[46] introduce the first component of activity recognition for a user's state to support future decisions towards adaptive control over devices.

### *4.3. The functions of decision-making algorithms in healthcare*

#### *4.3.1. Simple diagnose*

Diagnosis is one of the basic functions that decision-making algorithms are deployed on in the area of healthcare. For some illnesses, it is possible to take an automated diagnosis based on an algorithm. For example, Mahdi [35] illustrates the CDS (cognitive dynamic system) algorithm based on a decision-making system (ADMs) that is used in diagnosing Arrhythmia disease. These are similar to a doctor's decision process which are often based on checklists - getting "yes" or "no" answers from patients, and then classifying the disease. Such simple approaches are the basis for more complex smart home e-healthcare systems. For example, Prabal et al.[47] illustrates how a wearable device can be used to remotely monitor a patient's health in real-time. Based on the daily monitoring data, it can predict some diseases, such as diabetes.

#### *4.3.2. Simple screening*

Simple screening [48] is quite similar to simple diagnosis. Based on sensors, such approaches can replace some examinations that would normally be taken in a hospital. The difference between simple screening and simple diagnose is that screening attempts just to check whether patients are in good health condition, but they don't attempt to identify specific diseases. For example, Mahdi et al.[48] introduce a system that can "screen human health condition automatically between two binary (healthy and unhealthy) states based on subjects' single lead ECG traces". The benefits of simple screening and simple diagnose are that the underlying algorithms are rather simple to implement.They can be trained and take decisions very quickly (i.e. recommending to see a doctor) and the result is simple enough - healthy and unhealthy.

#### 4.3.3. Emergency alert

Decision-making algorithms can also help the doctors or caregivers to provide alert functions during emergency situations. Based on the degree of urgency, the system can decide whether to automatically notify family members, doctors or emergency medical providers. For example, in [47], if the value of THI (temporal health index) is above the threshold level, patients' family members are informed by generating warning alerts. Other projects investigate automatic fall detection, which is a common problem for elderly people living at home.

## 5. Discussion

Decision-making algorithms are a central AI function of smart home applications. According to our literature review, we can see that the functions of decision-making algorithm deployment range from very simple functions to more advanced functions with the goal of providing a personalized experience. In this progress, we can see that humans have to be considered in the decision-loops of the systems. However, while we have found many studies focusing on improving the quality of decision-making algorithms, we have seen few studies that focus on how humans interact with decision-making algorithms. Therefore, in RQ-2, we asked the question: what are the design challenges for human-in-the-loop decision-making algorithms in smart homes?

For our analysis, we refer to the framework of "human-centred AI" that has been suggested by Ben Shneiderman[49]. The goal of human-centred AI is not to replace humans entirely but to enhance our capabilities by way of intelligent, human-informed technology. Through its combination of the precision of machine learning with human input and values, human-centered AI is expected to be able to take more informed decisions. In his definition, human-centered AI aims at bringing AI under human control. It spans the whole range between full human control to full AI automation). In this definition, human-centered AI is to build collaboration between humans and AI to augment the AI system. Such approaches have been more and more recognized lately, as designers increasingly have to consider human aspects in the design of AI systems [50].

If we look at the functions provided by decision-making algorithms in the smart home, they all aim to achieve AI automation. For some functions, such as simple diagnose, screening, and anomaly detection, the computer will take a decision based on the data collected by the sensors and take action based on computation. For some functions, such as home appliances scheduling and controlling, they will not only automatically schedule the appliances, but also involve user feedback or preference into the decision-making algorithm process.In order to answer RQ2, we first identified three main efforts that designers and developers did in our review to involve humans in the loop. Then, we explain the needs of involving human in the loop. In the end, we illustrate the design challenges that designers and developers will face in designing human-in-the-loop decision-making algorithms in smart homes.

### 5.1. The current state of human-in-the-loop decision-making algorithms in smart homes

#### 5.1.1. Build dialogue between users and algorithms

We can see from the review, that for most of the identified functions, humans are rather out of the loop of the decision-making process. Zhang et al.[30] mention the challenge of how to include human behaviour in the loop of making control decisions. However, there is some application area – energy allocation between smart home and smart grid where developers are trying to get users' feedback from the consumer side to enhance the results of energy allocation. Another area is home appliances scheduling and controlling. In [44], the author tries to include user preferences into the decision-making algorithm, in order to handle the uncertainty of human preferences. Dietvorst et al. [51] show that allowing algorithmic predictions to be modified by humans can make humans more likely to use them.

#### *5.1.2. Be transparent about how outputs are generated*

Most of the studies we identified do not consider the transparency of the decision-making process of the algorithm. Only Sara et al. [52] provides a transparent decision-making procedure with significant predictive performance. For technology oriented works, accuracy is usually the biggest concern when building decision-making algorithms. Rene's paper [53] discusses how transparency influences the trust towards the algorithm result. Algorithm transparency makes humans understand the decisions or predictions made by the AI. It contrasts with the "black box" concept in machine learning where even its designers cannot explain why an AI arrived at a specific decision. If there is a lack of transparency of how outputs are generated, users might lose trust towards the results [54].

#### *5.1.3. Override the algorithm result if it takes action*

In Ben Shneiderman's[49] framework, the system can be divided into 4 categories: 1) high human control with high computer automation, 2) high human control with low computer automation, 3) low human control with high computer automation and 4) low human control with low computer automation. For some functions in healthcare, for example, simple diagnose or simple screening, the functions are fully automated with low human control, therefore, there is no need to override it because the system does not take any action. But for some functions, users might want to have the ability to override the algorithm results. For example, for controlling and scheduling home appliances, users may want to be the final decision maker even under fully automated systems. Hence, designers and developers should consider to give users the control towards overriding the results of automated decisions. From the review, only Nassourous et al. [55] consider to use a open-loop system which will include dependent control inputs or use a closed-loop system which will include user feedback for independent control inputs.

### *5.2. The needs of human-in-the-loop of decision-making algorithms in smart home*

We can observe how the deployment of the decision-making algorithms has gone from simple functions such as energy allocation or simple diagnosis to more advanced functions such as home appliances scheduling and controlling. With the development of AI systems, we can see several papers attempting to provide a more personalized experience in energy management and healthcare, which requires more advanced functions. For example, in the energy management area, Alisson et al.[36] suggest three modes for the users to select – comfort mode, standard mode and economical mode. In comfort mode, it is non-intrusive, as the system does not make any restrictions for using residential loads. Standard mode is the one that makes a little restriction on the use in certain scenarios of tariff and accentuated consumption. The Economical mode is the operation mode with the highest intrusion of the system in the disconnection of loads, it aims at users who wish to reduce the use of energy from the network, even in scenarios of low power generation. In the healthcare area, Zhang et al.[56] mention the concept of lifelong healthcare data management. Their system can take different decisions such as users' treatment times, and provide personalized lifestyle guidance based on these data. In the future, it is expected to provide users with recommendations for exercise actions and get users' feedback on recovery feelings to fill the gap in the after-medical-care phase. In these advanced features, we can see that humans are assumed to be more involved in the loop of decision-making processes. Similarly, Abdelilah Rochd[57] proposed the ideas to include human behavior into the control decision to build personalized preference profiles. There are two components in their system, one is the environment, and the other is the agent. Agents learns from the environment and makes decisions for the users. From this perspective, the author thinks it can involve users into the agent's decision-making process, or give rewards to the system. Another example is in HVAC, it gives users input towards how many occupants are in the environment to determine the HVAC control policy. With human and AI collaboration, such work can be done more efficiently.

### *5.3. The design challenges of human-in-the-loop of decision-making algorithms in smart home*

As mentioned by Wei Xu[58], history is repeating. When computers first appeared in the world, the development was very technology-driven by the developers. And when computers became popular, the concept of "human-centered design" [59] has been put up to solve the problems of user experience of computers. The same seems to be happening with AI: a lot of research is focusing on the accuracy of the algorithms, but as AI technology starts to be adopted on a bigger scale, "human-centered AI" [49] is becoming much more prominent.

We can see there are efforts from in the literature that we studied to put humans in the loop of decision-making algorithms, corresponding to the goals mentioned in HCAI [58], for example,"building dialogue between users and algorithm" and "override the algorithm results if it takes action" match the goal of providing human-controlled AI and human-driven decision-making, and "be transparent about how outputs are generated" corresponds to the goal of providing explainable AI. However, the efforts seem to be rather underrepresented, often lack systematic design considerations, and also rarely consider human needs in the beginning.

The goal of designing human-in-the-loop decision-making algorithms would be to combine human intelligence with machine intelligence to achieve better results, keeping humans as a part of the automated system [58]. There are two ways to achieve this goal: one is to involve humans in the decision loop of the system, the other is to involve human intelligence into the system which has been labelled as cognitive computing [60]. In this paper, we only focus on the first aspect. Therefore, in Table 1 and 2, we will analyse some issues of human and decision-making algorithms interaction in different context under the main issues category of HCAI [58]. With these challenges mentioned above in different context, we conclude three main challenges of designing human-in-the-loop decision-making algorithms in smart homes.

#### 5.3.1. *Accessibility to all users*

Within the context of smart home, accessibility becomes the main challenge for designing human-in-the-loop decision-making algorithms. It must consider all kinds of users, no matter their age, their technical expertise and their abilities. In the current situation, we seldom consider these questions, since the smart home has not yet come into popularity, but in the future, it will become the main challenge.

#### 5.3.2. *Different levels of user control*

We can see that the level of control from users' needs differs depending on the context of use. If the functions are not directly related to the needs of the users, such as the issue of energy allocation and anomaly detection, the control needs from users are not high. In the function of home appliances scheduling and controlling, users have the option to customize their usage of smart homes or allow the algorithms to make decisions automatically based on the training dataset results. Additionally the algorithms can evolve continuously with the collection of more data and feedback from the users, theoretically leading to ever more adapted systems based on the user's previous habits. Still, as we have discussed above, there is a need for users to have some sort of control over their algorithmic decision to some extent and that they can intervene into the process.

#### 5.3.3. *Personalization with acceptable privacy*

As we mentioned above, the future goal of decision-making algorithms in smart homes should be personalized to the needs and preferences of individual users. Especially in the light of ongoing debates about "surveillance captialism", this will pose the question of how to collect and analyze user data in a way that respects user privacy? In different contexts, for example, in healthcare, the closeness between humans and machines means the privacy issue will be the top concern in designing human-in-the-loop decision-making algorithms. The relationship is two-way: the machines need continuous input and feedback from users and the more data the users provide, the more privacy concerns the users might have. Therefore, in order to reach personalization, we should put the privacy issue at the top.

## 6. Conclusion

Based on the literature review and its analysis, we can see the ongoing development of AI systems with decision-making algorithms in two major application areas of smart homes – energy management and healthcare. We analyze what the functions of decision-making algorithms are: they are mainly used for energy allocation between smart grid and smart home, home appliances scheduling and controlling, energy consumption forecasting, simple diagnosis in healthcare, simple screening, real-time monitoring and diagnosis. In our analysis, we first identified the efforts of implementing human-centered AI in the literature review. On that basis, we illustrated challenges of implementing human-centered AI in different contexts in detail based on the umbrella of the main issues of HCAI. In the end, we conclude the three main challenges of implementing human-in-the-loop decision-making algorithms in smart homes. In the future, we will investigate how algorithmic decision-making and human-decision can cooperate together (hybrid intelligence) seamlessly in smart homes in more depth.

## 7. Acknowledgements

This work has been funded by the EU Horizon 2020 Marie Skłodowska-Curie International Training Network GECKO, Grant number 955422 (https://gecko-project.eu/).

## References

[1] Alam MR, Reaz MBI, Ali MAM. A review of smart homes—Past, present, and future. IEEE transactions on systems, man, and cybernetics, part C (applications and reviews). 2012;42(6):1190-203. Available from: https://doi.org/10.1109/TSMCC.2012.2189204.

[2] Teoh CC, Tan CE. A neural network approach towards reinforcing smart home security. In: 8th Asia-Pacific Symposium on Information and Telecommunication Technologies. IEEE; 2010. p. 1-5.

[3] Li D, Jayaweera SK. Reinforcement learning aided smart-home decision-making in an interactive smart grid. In: 2014 IEEE Green Energy and Systems Conference (IGESC). IEEE; 2014. p. 1-6. Available from: https://doi.org/10.1109/IGESC.2014.7018632.

[4] Yu L, Xie W, Xie D, Zou Y, Zhang D, Sun Z, et al. Deep reinforcement learning for smart home energy management. IEEE Internet of Things Journal. 2019;7(4):2751-62. Available from: https://doi.org/10.1109/JIOT.2019.2957289.

[5] Habal F, Huang V. a decision-making algorithm for the management of pregnancy in the inflammatory bowel disease patient. Alimentary pharmacology & therapeutics. 2012;35(5):501-15. Available from: https://doi.org/10.1111/j.1365-2036.2011.04967.x.

[6] Chouldechova A, Benavides-Prado D, Fialko O, Vaithianathan R. A case study of algorithm-assisted decision making in child maltreatment hotline screening decisions. In: Conference on Fairness, Accountability and Transparency. PMLR; 2018. p. 134-48.

[7] Yang Z, Ouyang T, Fu X, Peng X. A decision-making algorithm for online shopping using deep-learning–based opinion pairs mining and q-rung orthopair fuzzy interaction Heronian mean operators. International journal of intelligent systems. 2020;35(5):783-825. Available from: https://doi.org/10.1002/int.22225.

[8] De-Arteaga M, Fogliato R, Chouldechova A. A case for humans-in-the-loop: Decisions in the presence of erroneous algorithmic scores. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems; 2020. p. 1-12. Available from: https://doi.org/10.1145/3313831.3376638.

[9] Calero Valdez A, Ziefle M. Human factors in the age of algorithms. understanding the human-in-the-loop using agent-based modeling. In: International Conference on Social Computing and Social Media. Springer; 2018. p. 357-71. Available from: https://doi.org/10.1007/978-3-319-91485-5_27.

[10] Alaa M, Zaidan AA, Zaidan BB, Talal M, Kiah MLM. A review of smart home applications based on Internet of Things. Journal of Network and Computer Applications. 2017;97:48-65. Available from: https://doi.org/10.1016/j.jnca.2017.08.017.

[11] wikipedia. Internet of Things; 2020. Available from: https://en.wikipedia.org/wiki/Internet_of_things.

[12] Majeed R, Abdullah NA, Ashraf I, Zikria YB, Mushtaq MF, Umer M. An intelligent, secure, and smart home automation system. Scientific Programming. 2020;2020. Available from: https://doi.org/10.1155/2020/4579291.

[13] Guo X, Shen Z, Zhang Y, Wu T. Review on the application of artificial intelligence in smart homes. Smart Cities. 2019;2(3):402-20. Available from: https://doi.org/10.3390/smartcities2030025.

[14] Lee MK. Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. Big Data & Society. 2018;5(1):2053951718756684. Available from: https://doi.org/10.1177/2053951718756684.

[15] Mykel Kochenderfer TW, Wray K. Algorithms for Decision Making. MIT PRESS; 2022.

[16] Wang R, Harper FM, Zhu H. Factors Influencing Perceived Fairness in Algorithmic Decision-Making: Algorithm Outcomes, Development Procedures, and Individual Differences. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. CHI '20. New York, NY, USA: Association for Computing Machinery; 2020. p. 1–14. Available from: https://doi.org/10.1145/3313831.3376813.

[17] Schwarting W, Alonso-Mora J, Rus D. Planning and decision-making for autonomous vehicles. Annual Review of Control, Robotics, and Autonomous Systems. 2018;1:187-210. Available from: https://doi.org/10.1146/annurev-control-060117-105157.

[18] Srinivasan S, Kamalakannan T. Multi criteria decision making in financial risk management with a multi-objective genetic algorithm. Computational Economics. 2018;52(2):443-57. Available from: https://doi.org/10.1007/s10614-017-9683-7.

[19] Lakhno V, Malyukov V, Gerasymchuk N, Shtuler I. Development of the decision making support system to control a procedure of financial investment. - . 2017;6(3):35-41. Available from: https://doi.org/0.15587/1729-4061.2020.194531.

[20] Légaré F, Adekpedjou R, Stacey D, Turcotte S, Kryworuchko J, Graham ID, et al. Interventions for increasing the use of shared decision making by healthcare professionals. Cochrane database of systematic reviews. 2018;(7). Available from: https://doi.org/10.1002/14651858.CD006732.pub4.

[21] Lysaght T, Lim HY, Xafis V, Ngiam KY. AI-assisted decision-making in healthcare. Asian Bioethics Review. 2019;11(3):299-314. Available from: https://doi.org/10.1007/s41649-019-00096-0.

[22] Yang Z, Garg H, Peng R, Wu S, Huang L. Group decision algorithm for aged healthcare product purchase under q-rung picture normal fuzzy environment using Heronian mean operator. International Journal of Computational Intelligence Systems. 2020;13(1):1176-97.

[23] Kochenderfer MJ, Wheeler TA, Wray KH. Algorithms for decision making. MIT press; 2022.

[24] Cardil A, Monedero S, Schag G, de Miguel S, Tapia M, Stoof CR, et al. Fire behavior modeling for operational decision-making. Current Opinion in Environmental Science & Health. 2021;23:100291. Available from: https://doi.org/10.1016/j.coesh.2021.100291.

[25] Noonan-Wright EK, Opperman TS, Finney MA, Zimmerman GT, Seli RC, Elenz LM, et al. Developing the US wildland fire decision support system. Journal of Combustion. 2011;2011. Available from: https://doi.org/0.1155/2011/168473.

[26] Calkin DE, Thompson MP, Finney MA, Hyde KD. A real-time risk assessment tool supporting wildland fire decisionmaking. Journal of Forestry. 2011;109(5):274-80.

[27] Javaid N, Ullah I, Akbar M, Iqbal Z, Khan FA, Alrajeh N, et al. An intelligent load management system with renewable energy integration for smart homes. IEEE access. 2017;5:13587-600. Available from: https://doi.org/10.1109/ACCESS.2017.2715225.

[28] Ahn J, Cho S. Anti-logic or common sense that can hinder machine's energy performance: Energy and comfort control models based on artificial intelligence responding to abnormal indoor environments. Applied Energy. 2017;204:117-30. Available from: https://doi.org/10.1016/j.apenergy.2017.06.079.

[29] Parvez I, Sarwat A, Debnath A, Olowu T, Dastgir MG, Riggs H. Multi-layer perceptron based photovoltaic forecasting for rooftop pv applications in smart grid. In: 2020 SoutheastCon. IEEE; 2020. p. 1-6. Available from: https://doi.org/10.1109/SoutheastCon44009.2020.9249681.

[30] Zhang H, Wu D, Boulet B. A review of recent advances on reinforcement learning for smart home energy management. In: 2020 IEEE Electric Power and Energy Conference (EPEC). IEEE; 2020. p. 1-6. Available from: https://doi.org/10.1109/EPEC48502.2020.9320042.

[31] Huang Y, Wang K, Gao K, Qu T, Liu H. Jointly optimizing microgrid configuration and energy consumption scheduling of smart homes. Swarm and Evolutionary Computation. 2019;48:251-61. Available from: https://doi.org/10.1016/j.swevo.2019.04.007.

[32] Meng F, Zeng XJ, Zhang Y, Dent CJ, Gong D. An integrated optimization+ learning approach to optimal dynamic pricing for the retailer with multi-type customers in smart grids. Information Sciences. 2018;448:215-32. Available from: https://doi.org/10.1016/j.ins.2018.03.039.

[33] Thakur N, Han CY. An ambient intelligence-based human behavior monitoring framework for ubiquitous environments. Information. 2021;12(2):81. Available from: https://doi.org/10.3390/info12020081.

[34] Sun H, De Florio V, Gui N, Blondia C. Promises and challenges of ambient assisted living systems. In: 2009 Sixth International Conference on Information Technology: New Generations. Ieee; 2009. p. 1201-7. Available from: https://doi.org/10.1109/ITNG.2009.169.

[35] Naghshvarianjahromi M, Kumar S, Deen MJ. Brain-inspired intelligence for real-time health situation understanding in smart e-health home applications. IEEE Access. 2019;7:180106-26. Available from: https://doi.org/10.1109/ACCESS.2019.2958827.

[36] Souza AT, Canha LN, Milbradt RG, Lemos CL, Michels C, Santana TA. Intelligent demand response system integrated with micro generation and energy storage using machine learning and Internet of

Things concepts. In: 2019 IEEE PES Innovative Smart Grid Technologies Conference-Latin America (ISGT Latin America). IEEE; 2019. p. 1-6. Available from: https://doi.org/10.1109/ISGT-LA.2019.8895479.

[37] Garroussi Z, Ellaia R, Lucas Jy, et al. A matheuristic for a bi-objective demand-side optimization for cooperative smart homes. Electrical Engineering. 2020;102(4):1913-30. Available from: https://doi.org/10.1007/s00202-020-00997-6.

[38] Amini MH, Imteaj A, Mohammadi J. Distributed machine learning for resilient operation of electric systems. In: 2020 International Conference on Smart Energy Systems and Technologies (SEST). IEEE; 2020. p. 1-6. Available from: https://doi.org/10.1109/SEST48500.2020.9203368.

[39] Han T, Muhammad K, Hussain T, Lloret J, Baik SW. An efficient deep learning framework for intelligent energy management in IoT networks. IEEE Internet of Things Journal. 2020;8(5):3170-9. Available from: 10.1109/JIOT.2020.3013306.

[40] Vasudevan N, Venkatraman V, Ramkumar A, Sheela A. Real-time day ahead energy management for smart home using machine learning algorithm. Journal of Intelligent & Fuzzy Systems. 2021;41(5):5665-76. Available from: https://doi.org/10.3233/JIFS-189886.

[41] Li T, Fong S, Li X, Lu Z, Gandomi AH. Swarm decision table and ensemble search methods in fog computing environment: Case of day-ahead prediction of building energy demands using IoT sensors. IEEE Internet of Things Journal. 2019;7(3):2321-42. Available from: https://doi.org/10.1109/JIOT.2019.2958523.

[42] Jordehi AR. Binary particle swarm optimisation with quadratic transfer function: A new binary optimisation algorithm for optimal scheduling of appliances in smart homes. Applied Soft Computing. 2019;78:465-80. Available from: https://doi.org/10.1016/j.asoc.2019.03.002.

[43] Alhasnawi BN, Jasim BH, Esteban MD, Guerrero JM. A novel smart energy management as a service over a cloud computing platform for nanogrid appliances. Sustainability. 2020;12(22):9686. Available from: https://doi.org/10.3390/su12229686.

[44] Rossit DG, Nesmachnow S, Toutouh J, Luna F. Scheduling deferrable electric appliances in smart homes: a bi-objective stochastic optimization approach. 2021. Available from: https://doi.org/10.3934/mbe.2022002.

[45] Rashid RA, Chin L, Sarijari MA, Sudirman R, Ide T. Machine learning for smart energy monitoring of home appliances using IoT. In: 2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN). IEEE; 2019. p. 66-71. Available from: https://doi.org/10.1109/ICUFN.2019.8806026.

[46] Wang Z, Dogan S, Stolikj M, Kondoz AM. Towards adaptive control in smart homes: Overall system design and initial evaluation of activity recognition. In: 2017 Intelligent Systems Conference (IntelliSys). IEEE; 2017. p. 129-36. Available from: https://doi.org/10.1109/IntelliSys.2017.8324274.

[47] Verma P, Sood SK. Fog assisted-IoT enabled patient health monitoring in smart homes. IEEE Internet of Things Journal. 2018;5(3):1789-96. Available from: https://doi.org/10.1109/JIOT.2018.2803201.

[48] Naghshvarianjahromi M, Majumder S, Kumar S, Naghshvarianjahromi N, Deen MJ. Natural Brain-Inspired Intelligence for Screening in Healthcare Applications. IEEE Access. 2021;9:67957-73.

[49] Shneiderman B. Human-centered artificial intelligence: Reliable, safe & trustworthy. International Journal of Human–Computer Interaction. 2020;36(6):495-504. Available from: https://doi.org/10.1080/10447318.2020.1741118.

[50] Xu W. Toward human-centered AI: a perspective from human-computer interaction. interactions. 2019;26(4):42-6. Available from: https://doi.org/10.1145/3328485.

[51] Dietvorst BJ, Simmons JP, Massey C. Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science. 2018;64(3):1155-70. Available from: https://doi.org/10.1287/mnsc.2016.2643.

[52] Mohammadi S, Eliassen F, Zhang Y, Jacobsen HA. Detecting false data injection attacks in peer to peer energy trading using machine learning. IEEE Transactions on Dependable and Secure Computing. 2021. Available from: https://doi.org/10.1109/TDSC.2021.3096213.

[53] Kizilcec RF. How much information? Effects of transparency on trust in an algorithmic interface. In: Proceedings of the 2016 CHI conference on human factors in computing systems; 2016. p. 2390-5. Available from: https://doi.org/10.1145/2858036.2858402.

[54] Došilović FK, Brčić M, Hlupić N. Explainable artificial intelligence: A survey. In: 2018 41st International convention on information and communication technology, electronics and microelectron-

ics (MIPRO). IEEE; 2018. p. 0210-5. Available from: https://doi.org/10.23919/MIPRO.2018.8400040.

[55] Nassourou M, Blesa J, Puig V. Robust economic model predictive control based on a zonotope and local feedback controller for energy dispatch in smart-grids considering demand uncertainty. Energies. 2020;13(3):696. Available from: https://doi.org/10.3390/en13030696.

[56] Zhang L, Ren J, Yuan H, Yang Z, Wang W, Guo M, et al. Evaluation of smart healthcare systems and novel uv-oriented solution for integration, resilience, inclusiveness and sustainability. In: 2020 5th International Conference on Universal Village (UV). IEEE; 2020. p. 1-28. Available from: https://doi.org/10.1109/UV50937.2020.9426210.

[57] Rochd A, Benazzouz A, Abdelmoula IA, Raihani A, Ghennioui A, Naimi Z, et al. Design and implementation of an AI-based & IoT-enabled Home Energy Management System: A case study in Benguerir—Morocco. Energy Reports. 2021;7:699-719. Available from: https://doi.org/10.1016/j.egyr.2021.07.084.

[58] Maadi M, Akbarzadeh Khorshidi H, Aickelin U. A review on human–ai interaction in machine learning and insights for medical applications. International journal of environmental research and public health. 2021;18(4):2121. Available from: https://doi.org/10.3390/ijerph18042121.

[59] Boy GA. The handbook of human-machine interaction: a human-centered design approach. CRC Press; 2017.

[60] Zheng Nn, Liu Zy, Ren Pj, Ma Yq, Chen St, Yu Sy, et al. Hybrid-augmented intelligence: collaboration and cognition. Frontiers of Information Technology & Electronic Engineering. 2017;18(2):153-79. Available from: https://doi.org/10.1631/FITEE.1700053.

[61] Xiao G. Machine learning in smart home energy monitoring system. In: IOP Conference Series: Earth and Environmental Science. vol. 769. IOP Publishing; 2021. p. 042035. Available from: https://doi.org/10.1088/1755-1315/769/4/042035.

[62] Divya V, Leena Sri R. Intelligent real-time multimodal fall detection in fog infrastructure using ensemble learning. In: Challenges and Trends in Multimodal Fall Detection for Healthcare. Springer; 2020. p. 53-79. Available from: https://doi.org/10.1007/978-3-030-38748-8_3.

[63] Roy PN, Armin M, Kamruzzaman S, Hoque ME. A Supervisory Control of Home Appliances using Internet of Things. In: 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE). IEEE; 2019. p. 1-6. Available from: https://doi.org/10.1109/ECACE.2019.8679314.

[64] Khir NAM, Abd Malik NNN, Latiff NMA, Said DM, Hamzah SA. Smart Micro-Grid Delivery Response System via Internet of Things. In: 2019 IEEE 14th Malaysia International Conference on Communication (MICC). IEEE; 2019. p. 75-80. Available from: https://doi.org/10.1109/MICC48337.2019.9037590.

[65] Hussain SM, Zafar A, Khalid R, Abid S, Qasim U, Khan ZA, et al. An efficient scheduling of electrical appliance in micro grid based on heuristic techniques. In: Conference on Complex, Intelligent, and Software Intensive Systems. Springer; 2017. p. 164-73. Available from: https://doi.org/10.1007/978-3-319-61566-0_15.

[66] Rojek L, Islam S, Hartmann M, Creutzburg R. IoT-based real-time monitoring system for a smart energy house. Electronic Imaging. 2021;2021(3):38-1.

[67] Wang J, Srikantha P. Stealthy black-box Attacks on deep learning non-intrusive load monitoring models. IEEE Transactions on Smart Grid. 2021;12(4):3479-92. Available from: https://doi.org/10.1109/TSG.2021.3062722.

[68] Demirezen G, Fung AS, Deprez M. Development and optimization of artificial neural network algorithms for the prediction of building specific local temperature for HVAC control. International Journal of Energy Research. 2020;44(11):8513-31. Available from: https://doi.org/10.1002/er.5537.

[69] Alves MJ, Antunes CH. A semivectorial bilevel programming approach to optimize electricity dynamic time-of-use retail pricing. Computers & Operations Research. 2018;92:130-44. Available from: https://doi.org/10.1016/j.cor.2017.12.014.

[70] Mpawenimana I, Pegatoquet A, Roy V, Rodriguez L, Belleudy C. A comparative study of LSTM and ARIMA for energy load prediction with enhanced data preprocessing. In: 2020 IEEE Sensors Applications Symposium (SAS). IEEE; 2020. p. 1-6. Available from: https://doi.org/10.1109/SAS48726.2020.9220021.

[71] Chatrati SP, Hossain G, Goyal A, Bhan A, Bhattacharya S, Gaurav D, et al. Smart home health monitoring system for predicting type 2 diabetes and hypertension. Journal of King Saud University-Computer

and Information Sciences. 2020. Available from: https://doi.org/10.1016/j.jksuci.2020.01.010.

[72] van Berkel N, Skov MB, Kjeldskov J. Human-AI interaction: intermittent, continuous, and proactive. Interactions. 2021;28(6):67-71. Available from: https://doi.org/10.1145/3486941.

[73] Oyeleke RO, Yu CY, Chang CK. Situ-centric reinforcement learning for recommendation of tasks in activities of daily living in smart homes. In: 2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC). vol. 2. IEEE; 2018. p. 317-22.

[74] Igwe OM, Wang Y, Giakos GC. Activity learning and recognition using margin setting algorithm in smart homes. In: 2018 9th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). IEEE; 2018. p. 653-8. Available from: https://doi.org/10.1109/UEMCON.2018.8796766.

[75] Qu W, Tang J, Niu W. Research on fire detection based on multi-source sensor data fusion. In: International Conference on Mechatronics and Intelligent Robotics. Springer; 2019. p. 629-35. Available from: https://doi.org/10.3390/s22124550.

[76] Smart Firefighting System for Smart Cities Adopting Fog/Edge Computing. VOLUME-8 ISSUE-10, AUGUST 2019, REGULAR ISSUE. 2019. Available from: https://doi.org/10.35940/ijitee.j9920.0881019.

[77] Imteaj A, Amini MH. Distributed sensing using smart end-user devices: Pathway to federated learning for autonomous IoT. In: 2019 International conference on computational science and computational intelligence (CSCI). IEEE; 2019. p. 1156-61. Available from: https://doi.org/10.1109/CSCI49370.2019.00218.

[78] Klaus P, Zaichkowsky JL. The convenience of shopping via voice AI: Introducing AIDM. Journal of Retailing and Consumer Services. 2022;65:102490. Available from: https://doi.org/10.1016/j.jretconser.2021.102490.

[79] Jha DN, Alwasel K, Alshoshan A, Huang X, Naha RK, Battula SK, et al. IoTSim-Edge: a simulation framework for modeling the behavior of Internet of Things and edge computing environments. Software: Practice and Experience. 2020;50(6):844-67. Available from: https://doi.org/10.48550/arXiv.1910.03026.

[80] Kashef R. Enhancing the Role of Large-Scale Recommendation Systems in the IoT Context. IEEE Access. 2020;8:178248-57. Available from: https://doi.org/10.1109/ACCESS.2020.3026310.

[81] Djalaei B, Salehi ME. Optimizing embedded neural networks based on saturated states. In: 2018 Real-Time and Embedded Systems and Technologies (RTEST). IEEE; 2018. p. 24-30. Available from: https://doi.org/10.1109/RTEST.2018.8397075.

[82] Kumar C, Mahdi HF. A real time algorithm for the machine to machine communication-smart warrior system. In: 2017 IEEE 13th Malaysia International Conference on Communications (MICC). IEEE; 2017. p. 213-7. Available from: https://doi.org/10.1109/MICC.2017.8311761.

[83] Wolf C, Blomberg J. Evaluating the promise of human-algorithm collaborations in everyday work practices. Proceedings of the ACM on Human-Computer Interaction. 2019;3(CSCW):1-23. Available from: https://doi.org/10.1145/3359245.

[84] Salvi S, Geetha V, Kamath SS. Jamura: a conversational smart home assistant built on Telegram and Google Dialogflow. In: TENCON 2019-2019 IEEE Region 10 Conference (TENCON). IEEE; 2019. p. 1564-71. Available from: https://doi.org/10.1109/TENCON.2019.8929316.

[85] Dahlgren K, Pink S, Strengers Y, Nicholls L, Sadowski J. Personalization and the Smart Home: questioning techno-hedonist imaginaries. Convergence. 2021;27(5):1155-69. Available from: https://doi.org/10.1177/13548565211036801.

[86] Ashenov N, Myrzaliyeva M, Mussakhanova M, Nunna HK. Dynamic Cloud and ANN based Home Energy Management System for End-Users with Smart-Plugs and PV Generation. In: 2021 IEEE Texas Power and Energy Conference (TPEC). IEEE; 2021. p. 1-6. Available from: https://doi.org/10.1109/TPEC51183.2021.9384980.

[87] Zhu J. Development Strategy of Artificial Intelligence Technology in the Field of Ice and Snow Sports. In: International Conference on Application of Intelligent Systems in Multi-modal Information Analytics. Springer; 2021. p. 619-26. Available from: https://doi.org/10.1007/978-3-030-74811-1_89.

[88] Zhou Z, Yu H, Shi H. Human activity recognition based on improved Bayesian convolution network to analyze health care data using wearable IoT device. IEEE Access. 2020;8:86411-8. Available from: https://doi.org/10.1109/ACCESS.2020.2992584.

# A. Appendix

Table 1.: Summary of main challenges for human interaction with decision-making algorithms in energy management

| Main Issues | Energy Allocation/Energy consumption forecasting /Home Appliances scheduling and controlling /Anomaly detection/Device management |
|---|---|
| Machine Behaviour | Handle unexpected outcome within system. |
| Human-machine collaboration | Investigate what kinds of collaboration energy management system needs to improve its results. |
| Machine intelligence | Design different engagements to involve human in the loop, for example, for energy allocation, users might expect low-level engagement, for home appliances scheduling and controlling, users might expect high-level engagement. |
| Explainability of machine output | Set different kinds of explainability towards different kinds of function. |
| Autonomous characteristics of machines | Handle some situation when the operation is not as expected |
| User interface | System may set the feedback invisible to avoid interruption. |
| Ethical design | Set different kinds of decision-making authority towards different functions. |

Table 2.: Summary of main challenges for human interaction with decision-making algorithm in e-healthcare

| Main Issues | Simple diagnose / Simple screening / Emergency alert |
|---|---|
| Machine Behaviour | Support unexpected outcome for elder person. |
| Human-machine collaboration | Form the long-term collaboration between machine and human to build human's trust and get continually human data input. |
| Machine intelligence | Involve users into the system to make users final control towards decisions that machines make. |
| Explainability of machine output | Explain to the end users of the process of machine decision - diagnose/screening/alert |
| Autonomous characteristics of machines | Handle with unanticipated situation especially emergency situation. |
| User interface | Handle with different devices - mobile, smartwatch, tablet with different interaction modes - voice, text, picture, even gesture in a system. |

| | |
|---|---|
| Ethical design | Privacy issues are significant in healthcare and also the authority of decision-making. |

Table 3.: The overview of decision-making algorithms application area in smart home

| Application Areas | Papers |
|---|---|
| Energy management | [61] [46] [62] [44] [42] [32] [30] [63] [40] [57] [37] [45] [57] [44] [36] [64] [39] [41] [43] [65] [66] [67] [68] [69] [52] [70] [38] |
| Healthcare | [33] [71] [72] [56] [73] [48] [47] [35] |
| Others | [74] [75] [76] [77] [78] [4] [79] [80] [62] [81] [82] [83] [84] [85] |

Table 4.: The functions of decision-making algorithms in energy management

| Functions | Papers |
|---|---|
| Energy allocation | [62] [38] [37] [76] [32] |
| Home appliances scheduling and controlling | [39] [69] [44] [42] [57] [86] [44] [43] [13] [63] [41] [45] [87] |
| Energy forecasting | [82] [39] [70] [66] |
| Energy forecasting and anomaly detection | [61] |
| Anomaly detection | [52] [67] |
| Device Management | [50] [62] |

Table 5.: The functions of decision-making algorithms in healthcare

| Functions | Papers |
|---|---|
| Simple diagnose | [47] [83] [71] [88] [73] [35] |
| Simple screening | [48] |
| Emergency alert | [33] |