The Cornerstones of Smart Home Research for Healthcare

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Abstract The aging of the world population has a strong impact on the world wide health care expenditure and is especially significant for countries providing free health care services to their population. One of the consequences is the increase in semi-autonomous persons requiring to be placed in specialized long term care centers. These kinds of facilities are very costly and often not appreciated by their residents. The idea of "aging in place" or living in one's home independently is a key solution to counter the impact of institutionalization. It can decrease the costs for the institutions while maximizing the quality of life of the individuals. However, these semi-autonomous persons require assistance during their daily life activities that professionals cannot hope to completely fill. Many envision the use of the smart home concept, a home equipped with distributed sensors and effectors, to add an assistance

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layer for these semi-autonomous populations. Still, despite years of research, there are several challenges to overcome in order to implement the smart home dream. This chapter positions itself as an easy to read introduction for readers unfamiliar with the challenges faced by computer science researchers regarding this difficult endeavor. It aims to walk the reader through the cornerstones of smart home research for health care.

Keywords Smart home · Aging in place · Activity recognition · Activity prediction · Context awareness · Dynamic service

1 Introduction

In western societies, the aging of the population is expected to have a major impact on the economy, society, and health care system over the next 30 years. This new reality can be considered as the most significant social transformation of the twenty-first century, with implications to many sectors, especially in the field of housing [53]. World Health Organisation (WHO) defines active aging as the process of optimizing opportunities for health, participation and security in order to enhance quality of life as people age [55]. Although aging does not necessarily imply illness or disability, the risk of both does increase. Despite these risks, elders usually prefer aging at home rather being placed in long term care facilities [35]. Therefore, the main consequence of an aging population is that affordable senior housing with supportive services remain a key component to the worlds long-term care continuum. Nevertheless, many challenges arise if one wants to provide adequate services to these semi-autonomous populations. The fundamental question is then how to provide cost-efficient adapted care services at home to a growing number of elders considering the increasing staff shortage in the field of health care [8].

Technology can certainly be part of the solution to this challenge. From that perspective, the home environment could be adapted using intelligent technologies and sensors to offset cognitive and physical deficiencies, to provide assistance and guidance to the resident, and to support the caregivers [9]. This vision of the future, which has now become a reality, originated in 1988 at the Xerox Palo Alto Research Center (PARC), resulting in the work entitled "The Computer for the 21st Century" by Mark Weiser [54]. From the early 1990s, a large community of scientists developed around this specific research niche [8], actively seeking technological solutions for these very human problems by employing such concepts as ubiquitous sensors, ambient intelligence (AMI) and assistive technologies to keep people in their homes. This concept took the form of what we now know under the name of "smart homes" [45]. A smart home is a home extended with pervasive technologies to provide relevant assistance services to its residents [18]. In our context, the aim is to increase autonomy, enhance comfort, improve sense of safety, and optimize resource management for both the elders and the caregivers [25, 40]. For instance, a smart home could support elders in their activities of daily living while informing caregivers when help is required. Thanks to a complex infrastructure of sensors and reasoning, a home becomes aware of what is going on, and if needed, it can provide near real-time advices for completing activities safely.

The goal of this chapter is to introduce the reader to the research on smart home for assistance to semi-autonomous population. On one hand, this particular context offer several opportunities, but, on the other hand, it creates challenges that must be solved in order for the technology to gain traction. While it is by nature a very multi-disciplinary field of research, this chapter contributes by reviewing the cornerstones in research on smart home for health care from a computer science point of view [5]. This chapter should not be seen as a literature review on these challenges, but as mandatory work to understand why there are still so many research teams working on these subjects despite all the progress that as been made in the recent state-of-the-art. Therefore, the remaining headwinds are described assuming the reader has a basic knowledge of each of the topics discussed in the chapter. Finally, as the reader will see in the discussion section, there are several other issues with smart homes for assistance that are beyond the scope of this chapter (e.g. the business model), but are nonetheless important.

In the next section, the reader is introduced to the foundations of smart home research and the key fundamental elements are described. Thereafter, the chapter reviews the three main challenges in developing smart homes. The first challenge is how to recognize the ongoing activities of daily living of the person. The second challenge is how to learn, predict, and adapt over time using historical data. The third is how to develop dynamic services delivery in order to adequately provide assistance when needed to the resident. Finally, the chapter concludes with a discussion on other challenges in smart homes and with some perspectives on the future directions of research.

2 Foundations of Smart Homes

Smart homes represent a promising solution to enable aging at home in our society. However, for the technology to be adopted, the services it provides must be reliable and the assistance must be relevant for the end users [41]. Thus, multiple challenges arise in the development of smart homes. They range from hardware that must be reliable (through self monitoring and *ad hoc* networking [46]) to software and AI algorithms that must infer relevant context-aware assistance opportunities. Trying to cover all of these issues would require a complete book on the subject, but, in computer science, three issues are particularly important for the technology to work. Before discussing them into details, it is important to define the concept of smart home we adopt and to go through a brief history of the work done in the last few decades.

2.1 A Pervasive Infrastructure for Ambient Intelligence

In a smart home, a pervasive infrastructure relies on sensors and actuators placed at strategic locations. Services to residents are then personalized based on their needs and requirements [23, 54]. The sensors gather low-level information on actions performed in the home: movement detectors sense human presence; contact sensors inform when doors are open or closed; pressure sensors are triggered when one lies on a bed; flow meters monitor when the toilet is flushed or when the dishwasher is started; RFID readers identify and track tagged objects [20]. Such low-level information can then be analyzed to infer the progress of high-level activities (see Sect. 3), those performed correctly, erroneous ones, and even those not performed at all. Assistance can then be provided, if necessary, helping people to complete their activities, correcting errors, preventing risks, or sending alerts to caregivers (see Sect. 5). Such assistance opportunities are highly dependent on the quality and the granularity of the information inferred from the low-level sensors [15].

In the literature, research on smart homes as well as their services and objectives take many forms. The MIT's Smart Room is considered to be the first intelligent housing laboratories to offer assistance services [39]. It was used mainly to develop a set of computer programs necessary for the recognition of facial expressions and gestures. The Adaptive House [37], from Mozer et al., is a self-programmable house that adapts to the individual's daily routine. Another similar project, the Aware Home [32], aims to produce an environment capable of understanding the parameters and the properties of the housing facility and the place where different activities of the inhabitant are carried out to better take into account the activities of everyday life in a habitat. The CASAS smart home [17] is modeled as an intelligent agent that has goals, perceives and pilots its environment. Its objective is to enable aging in place while improving the comfort of its residents and reducing the energy requirement. The LIARA [11] and DOMUS [40] smart homes were first designed to play the role of a cognitive orthotics for populations afflicted with a cognitive impairment. They both aimed at high granularity activity assistance as opposed to other projects, such as GatorTech [26], which supports residents at a high level of abstraction (by providing health related metrics or a decision support system for example).

There is no commonly accepted definition of what a smart home is in the literature, and very often, the challenges are subjectively defined by the researchers through the goal they aim to achieve with the technology. In our case, we adopt the point of view of smart homes for fine grained assistance in the daily life of the resident (e.g. helping the resident to complete a recipe or assisting with the realization of a rehabilitation program); not only as a tool to ensure security or measure the resident's health status. It is important for the reader to understand this in order to understand the challenges identified in the state-of-the-art that are described through this chapter.

3 Activity Recognition for Ambient Assistance

Recognizing human activities in smart homes plays an essential role for the purpose of assistance. With pervasive sensor networks and ambient intelligence technologies [17], sensor-based smart homes may analyze ambient changes caused by human behaviors, and provide appropriate services, supports, feedbacks, preventive warnings or interventions for their residents at the right time by means of context-aware applications [9]. An *activity recognition module* is an inference system that tries to find, among all defined activities models, the one that best explains the detected actions, which are, themselves, inferred from the set of low-level sensors (Fig. 1). Despite efforts over the past decades, activity recognition remains a challenging task for the scientific community due to the particular characteristics and the flexible designs of smart homes. Some of the most important difficulties faced by researchers are described below.

Diversified Data Types. To monitor and capture ambient conditions as comprehensively as possible, heterogeneous sensors are ubiquitously deployed in smart homes. Because of no uniform specification, captured sensor data may be discrete, continuous, nominal (categorical), binary, ordinal or numeric [10]. Thus, it is necessary to choose appropriate methods to handle these heterogeneous data.

Large-Scale Data. In smart homes built on a decentralized architecture, devices and sensors mutually communicate and exchange information all the time. Ambient changes are memorized as multi-dimensional data. The temporal and sequential data is usually noisy and numerous. On this account, an activity recognition program not only requires efficient methods to handle large-scale data, but also effective preprocessing such as feature selection to reduce dimensionality [27]. Moreover, very often the data is too big to be stored permanently and thus the algorithms may need to be able to work with incomplete history or with streams of data.

Unreliable Data Source. For many unpredictable events, captured sensor data is not always reliable. The sensors' values may be anomalous due to misreading,

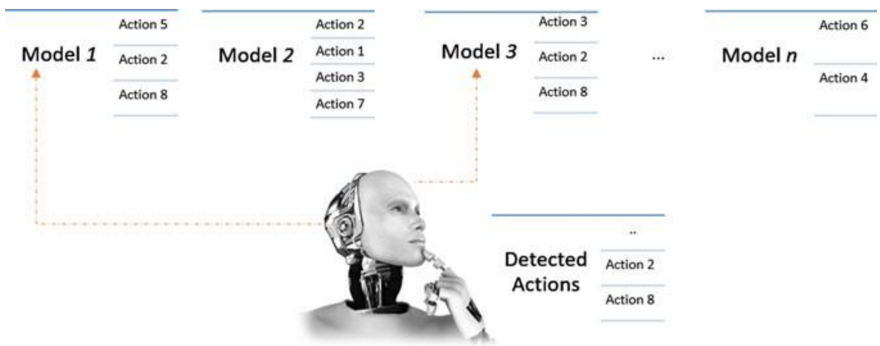

Fig. 1 Activity recognition system

insensitivity or failure of sensors themselves [46]. Moreover, the situations of signal overlapping or mutual interference could not be totally avoided. In the case of multiple residents, the values are also easy to be affected by one or more residents. Besides, even if all the information collected are reliable, there is always redundant data caused by frequent sampling and repeatedly triggering, dispensable data caused by unnecessary sensors, or reversible contextual order due to loose causal constraints between two sequential data.

Various Behavioral Patterns. Human behaviors are basically performed in sequential and complex ways. Thus, captured sensor data is usually continuous without clear boundaries. Consequently, it is difficult to segment sensor data by activities in the recognition process. Moreover, an activity could have many particular ways to be achieved. The ways here are defined as patterns (or sequences of sensor events). Based on different living habits or personal preferences, an activity could have multiple behavioral patterns describing it.

Various Granularity. The activities of daily living (ADLs) can be classified as basic or instrumental [30]. Basic activities refer to essential self-maintaining tasks like feeding, dressing, or grooming. However, these activities are usually mutually exclusive, and difficult to assist adequately due to few component actions and short execution times. In contrast, the instrumental ones involve more actions, and need more planning and interactions. Most of the state-of-the-art literature focus on recognizing the ADLs on a broad abstract level (e.g. cooking). This coarsely grained recognition does not allow for multiple assistance opportunities [15]. This granularity problem, in the authors' opinion, is the number one limitation of current activity recognition methods.

Multiple Activities. When a resident tries to perform more than one activity over a period of time, there are three alternative ways: sequential, interleaved, or concurrent modes [47]. The method of discrimination is to analyze the composition of sequences, and the contexts among sensor data. Additionally, the complexity of recognition increases when there are multiple residents in smart environments. All the residents could be performing their own activities in parallel with the three aforementioned modes, or cooperate to accomplish joint activities with other residents. Then, the captured data may belong to one or more residents, and it is hard to determine which resident triggered a sensor event. Figure 2 demonstrates few of these scenarios and their inherent complexity.

3.1 Principal Solutions

It is challenging to summarize the literature on human activity recognition, especially since the best techniques depends on several factors that cannot be readily compared (e.g. ADLs granularity, type of sensors used, online versus offline recognition, etc.). They are often separated into two families: data-driven approaches and

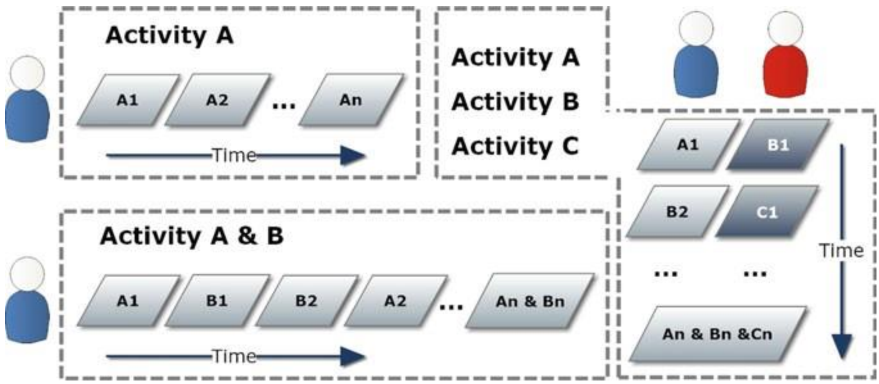

Fig. 2 Various ADLs scenarios and there timeline

knowledge driven approaches [15]. Mainstream data-driven solutions for activity recognition use both statistical and probabilistic reasoning such as hidden Markov models (HMMs), conditional random fields (CRFs), Bayesian networks, and their variations [4, 14]. These methods work fairly well in the field. However, reliable transition probabilities and emission matrices depend on a large amount of training data having stable probability distributions [10]. As a consequence, their results are sensitive to unbalanced distributions [24]. Researchers have tried in the past to deal with such imbalance, for example in [21]. Most of the other solutions are driven by prior domain knowledge, predefined rules or logic expressions [56]. Typical ones are usually to build ontological models based on knowledge representation languages such as the Web Ontology Language Description Logic (OWL-DL), or customized public ontologies [43]. Nevertheless, the definition, customization, maintenance, and extension of knowledge-driven models normally need significant artificial costs because they require human interventions from domain experts [16].

Given this weakness of knowledge-driven methods, some methods try to automatically generate the knowledge or the rules. They emphasize the analysis of occurrences and similarities about particular contexts or sensor events inside sequences. With this objective, they summarize and reuse historical data to look for regular patterns or hidden correlations in order to match new patterns with previous similar cases. The frequent pattern mining is the main solution to discover and group similar patterns [42]. Recently, several authors [24] have proposed an inference engine based on formal concept analysis that maximizes and extracts ontological correlations between patterns, and then clusters them to construct a graphical knowledge base. Sometimes, knowledge-driven methods use the data-driven ones as extensions to form a hybrid approach [6, 44].

To conclude, no method to this day exist that could completely solve the difficulties regarding activity recognition in smart homes. Knowledge driven approaches are complex to build and are time consuming. *Ad Hoc* algorithms are often working better than general algorithms, but they are not reusable. Probabilistic and statistical methods require a lot of historic data and pure machine learning methods provide a form of blackbox models difficult to exploit in assistance systems.

4 Learning and Predicting the Habits over Time

As discussed in the previous section, the activity recognition system is a core component of the artificial intelligence of a smart home for health care. It is one of the cornerstones which are necessary to provide the adequate assistance services. In order to be fully operational, however, the smart home should include other functionalities aiming to address several additional problems which go beyond the normal timeline:

- What if the observed person is performing an activity that does not exist in our activities models, or performing it in a very different way?
- What happens if the observed person is unable to start a required activity, such as taking medication?

These problems refer to a complementary task to the activity recognition which is often called the *prediction step* [34]. This part of the system is to adopt a dynamic and personalized approach for creating activities models; a task well-suited for machine learning techniques. With such a module, the system could be able to remind the assisted person to start an activity in case of forgetfulness or inability to initiate it.

4.1 Emergence of Machine Learning

The first activity recognition systems avoided the creation of activities models by assuming that they already had the complete library of activities in their knowledge bases [31]. However, creating such a large database containing all possible activities, with all different ways to perform them, is impossible to scale, slow and costly in human resources. On the other hand, machine learning algorithms are well-suited for finding frequent sequences [50]. If we consider the activities as ordered sequence of activated sensors, using a history log of activated sensors the task of creating the activities' models can be automated such as in [12, 28].

Besides the creation of activities models, machine learning techniques can also capture very useful information that can improve classical activity recognition. For example, the usual starting time or ending time of an activity could be learned. From the model on the Fig. 1, with the detected actions 2 and 8, the activity recognition system still could not choose between model 1 and 3. However, if we know that activity 1 is usually performed at 10 a.m., activity 3 at 6 p.m. and the current time is 9:55 a.m., activity 1 will be chosen because it is more likely. This is obviously a very simple example, but the idea can be used for more complex scenarios.

Average time between two adjacent sensors of an activity can also be very useful. It can help decide activating an effector, for offering assistance, when this time is exceeded without detecting the activation of the second sensor. It can also help differentiate activities. For instance, consider two sensing events produced by a smart power analyzer: ON (for boiling water), followed by OFF five minutes later. Then it can be inferred that the activity being performed is making coffee or tea. However, if the events are separated by more than ten minutes, maybe an error was made or maybe the person is doing something else. The time can also be used to check whether an action of another activity can be performed before the activation of the second sensor (cross-linked activities).

4.2 Activity Prediction

As we discussed in the previous section, the goal of a good activity recognition systems for smart home assistance is to be able to recognize the ADLs with a high granularity in order to provide useful assistance services. Therefore, ideal activity recognition systems should be able to detect actions in order to infer the activity being performed. If a prediction stage does not precede the recognition one, the system cannot assist the home occupant when no action is detected. This may happen to everyone, especially elderly people who forget to perform an important activity, or cognitively impaired patients who are even susceptible to initiation errors which prevent them from starting an activity [7].

Activity prediction stage can be designed in different manners. In [28], Allen temporal relations [3] were used to produce some rules of the kind: activity 1 precede activity 2, etc. So, when activity 1 is detected, activity 2 is predicted to be next. In contrast, in [36], starting times of each activity of each day are organized as a time series and techniques like ARIMA and VAR are used to predict activities starting times for the next day. Using time series for predicting activities starting times helps not only in assisting the smart home occupant even when no action is detected, but it also accelerates activity recognition by reducing the number of activities models that will be considered during activity recognition. Referring back to our previous example, at 9:55 a.m., model 3 will not be considered among activities models (its starting time is far different from current time), which means less comparisons and a faster activity recognition system. In order to reduce the number of considered activities models, activity prediction may also use spatial data, as in [13]. Knowing the smart home's location excludes activities that occur outside that location. For example, if the resident is in the bedroom, it can be assumed that he is not taking a shower.

When humans are observing another person performing some actions, they spontaneously use various kind of information in order to assist the person adequately (e.g., time, location, tools used). In the same way, the ambient agent must use all types of data that can be obtained for a robust and real-time assistance system in a smart home. Enriched by this information, a prediction system can further improve the ability of the assistive system to help the resident.

5 Dynamic Service Delivery for an Active Resident

Smart homes include a large range of interaction devices, from computers, televisions and smart phones to embedded display in Internet-of-Things (IoT) devices. Each of these types of devices represents an opportunity to interact with the residents, for specific tasks (e.g. a fridge) or polyvalent ones (e.g. smart phones). To assist the resident in their smart home, or across their daily living activities outside of the home, context-aware and intelligent systems are required to provide active assistive services, depending on their current whereabouts, their profile (e.g. preferences, physical or cognitive limitations), the context and the available devices. A context-aware system is a system that has the ability to capture, model and use specific information about the environment surrounding the system, such as location, time, user profile, environments topology [19].

5.1 *Desirable Properties of a Service Delivery System*

An intelligent service delivery system allows dynamic, fast and adapted service deployment toward the users in the environment, based on the context of the environment, and takes into account different constraints such as the users' capabilities and their preferences. We view the main goal of a service delivery system as supporting the deployment of assistive services into the smart environments for other smart systems like activity recognition or error and failure recognition systems [47]. These systems use the service delivery functionalities by sending a deployment or an activation request to the service delivery system, by supplying the information related to the assistance that needs to be deployed: Which user? Which software? What are the software needs? Is there a specific zone of the environment that is targeted by the assistance request? What is the current user activity? Is it a low priority or a high priority service delivery? and so on. To do so, directive or recommended based service delivery approaches are available, depending of several factors: context, type of services to deploy, user profiles, type of devices, etc. There are several challenges toward building a context-aware service delivery system.

Complexity of the Environment. The complexity of smart environments with their heterogeneous devices, specific configurations, and the important quantity of information to process, turn the service delivery into a serious challenge when real-time and context precision are some of the systems requirements [48]. Adaptable platforms are required to support the *ad hoc* use of devices that were not planned for at the design level [1]. Ideally, any device should be supported and their specific requirements should be downloaded dynamically in order to provide guidance to the system for adjustment. Deploying systems that provide a *plug and play* way to provide service delivery, by managing all the configurations and device heterogeneities, can help to a broader deployment and usage of the smart environment technologies.

Integration of the Service Delivery System. Another challenge is about the integration of a context-aware service delivery system into a smart home. These systems, made to be highly flexible, can be complex and difficult to adapt to specific software [38]. However, the service delivery system plays the role of a *glue* inside a smart home; it carries information between all the other systems and the end user. Since no standard exists to communicate the information between smart home systems (regarding information formatting especially), this task can be very arduous.

5.2 Current and Past Efforts for Service Delivery

Numerous efforts have been made in the development of platforms to support the delivery of assistance or services in the context of smart homes and ambient intelligence. The first works to describe the service delivery in smart environments were published around the beginning of this century, such as the Microsoft's `EasyLiving` project [49]. In this project, the researchers proposed the `EasyLiving Geometric Model` (EZLGM), a mechanism that determines which devices, in a given environment, can be used by a user during human-machine interactions and help in the selection of the right devices. The EZLGM models the relation (with measurements which describe the position and the orientation of an entity's coordinate frame) between entities, then uses geometrical transformations to determine if there is a relationship between entities.

More recently, Syed et al. [51] proposed an architecture for organizing autonomous software processes among devices of a smart space. To do this, the authors proposed the use of an intelligent system which is based on a knowledge representation of the system entities divided into four types of data: recipes, capabilities, rules, and properties. At the arrival of a service delivery in a smart space, the system compares the context of the query with the contexts of basic recipes. If the conditions in the recipe are checked and there is the presence of a device that can fulfill the requirements, a deployment policy is implemented.

In these previous systems, it is possible to impose the services to users or recommend services with different techniques. Using the context-aware models and recommendation algorithms to provide services or contents, Adomavicius et al. [2] was one of the first to propose context-aware recommender system which works on integrating contextual information in a multidimensional analysis of the users' preferences (in collaborative filtering) depending of the period of the day. Other works have been done on location-based recommender systems. For instance, Levandoski et al. [33] proposed a solution based on three types of location ratings (spatial rating for non-spatial items, non-spatial rating for spatial items, and spatial rating for spatial items). This approach is similar to the work of Adomavicius, where they used four-tuples or five-tuples to specify the ratings and used multidimensional analysis techniques to compare ratings, but with an extended definition of the context.

Finally, the `Tyche` project [22] is a distributed middleware that is made to be deployed on device nodes within smart homes and to allow the automatic deployment and management of software on environment nodes based on the device capabilities and users' profile. To automatically manage the service delivery, the middleware analyzes the contextual information of the environments, provided by the different device nodes and sensor networks, to find which devices would fit best for hosting the services. To fulfill the service delivery, `Tyche`'s reasoning mechanism uses four main contextual elements to deploy services toward the users: the profiles of devices in the environment, the logical configuration of the environment, the user profiles, and the software profiles. Finally, all these components are present in the smart environments at different (or not) locations and are related to contextual zones. Therefore, the goal of the `Tyche` service delivery mechanism is to manage all this information and find the optimal organization scheme to provide the services.

6 Discussion

As we discussed in the introduction, the smart home dream is now almost three decades old. Despite this fact, most of the smart home initiatives for health care never leave the ground of the research laboratories. There are still difficult problems arising in computer science to build an artificial intelligence for assistive smart homes. Three sections were dedicated to the three most important challenges in this chapter (Sects. 3–5). However, we selected other issues that are linked to the core problems of smart home research, and summarized them below. The authors hope to provide the readers with opportunities to further explore the topic of smart homes for aging in place with these selected issues.

6.1 Heterogeneous Hardware

A wide spectrum of equipment types and manufacturers are available, leading to much heterogeneity between hardware, networks, and applications [29]. Since a single manufacturer cannot typically address all needs and contexts, many technologies have to coexist and must cooperate. The software architecture must then allow to integrate such an eclectic variety of equipments, protocols, and services to ensure transparency with respect to information exchange, applications and services. This situation is also known as the *vertical handover* [57].

6.2 Ethics

Social and ethical concerns result from ubiquitous technology within smart homes [52]. First, technological dependencies may impede individuals instead of fostering autonomy. Relying too much on assistance may lead to withdraw oneself from completing activities on their own, expecting the smart home to compensate their deficits. Smart home assistance could also undermine an elder's freedom by offering and even choosing only specific solutions. Finally, surveillance can put privacy at risk. Seamless integration and ubiquity of sensors can affect one's ability to detect their presence and knowing exactly what is monitored or not. Moreover huge memory capacity of computers could allow to set up surveillance that could persist across time and space, more than necessary.

6.3 The Stakeholders' Dilemma

Finally, one very difficult issue regarding smart home for health care is very rarely discussed. The stakeholders' dilemma refer to the disruptive nature of these new technologies. There are currently no business models for the smart home and it is far from clear who is going to pay to implement the smart homes to assist the elders. Will it be the government through public health spending? Insurances? Or should it be left to private corporation? An open-mind must be kept regarding the business model.

7 Conclusion

This chapter presented the cornerstones of smart home research for health care with a specific emphasis on computer science difficulties regarding the construction of an artificial intelligence in smart homes. Smart homes are a challenging endeavor, and while the literature has progressed a lot on all of the topics presented, there are still several issues to overcome in order to implement the smart home dream. In particular, the cornerstones of smart home research for healthcare are the activity recognition, the learning and the prediction of the behaviors over time, and the context aware service delivery. The AI discussed in this paper was, however, the ideal one. The lack of ideal solutions does not mean that smart homes could not prove useful in the present. Smaller, simpler smart homes can be implemented to provide services to semi-autonomous residents, provided an adequate business model is found. Future work should address this important question.

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