Enrichment of Smart Home Services by Integrating Social Network Services and Big Data Analytics

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***Abstract*—Smart homes have gained attraction for several years in people's daily lives and are still increasing. They provide a fruitful foundation for the creation of social network services as they escort habits and regular activities of people at home, along their way or even at work. Smart homes and their current development stage are not only able to support people by intelligent functionality but also to predict the behavior or even the interaction with the social network of a person. For that, smart home technology makes strong use of big data techniques that help to master the vast amount of data generated continuously. In this paper we conduct a literature research that investigates the current state-of-the-art of smart homes and the related generation of social network services in a big data driven environment. We reveal future research opportunities that emerge from the combination of mastering big data in smart homes and, hence, provide design recommendations for social network services.**

***Keywords*-Smart Home; Big Data Analytics, Ambient Intelligence; Social Networks; Social Network Services**

I. Introduction

A. Motivation

A topic that will strongly influence our everyday life in the next years is smart homes. Their purpose is to assist residents in their daily lives, in the field of healthcare, entertainment or energy consumption [1]. Even if the concept of smart homes emerged in research several decades ago, the technological progress in ubiquitous and pervasive computing in the recent years facilitated its feasibility and has made it ready for the consumer market [1], [2], [3]. Consequently, an increasing amount of researchers has begun investigating the field of smart homes. Further, they gain from social technologies and their resulting behavior of their users, like giving recommendations of what movies to watch to friends that they might have never met. These social services have dramatically changed the way of how people interact privately and publicly, engage in shopping or adapt their informational and self-presentational behavior [4]. Supporting the entertainment domain of smart homes is therefore only a small area of application for such disruptive technology. It has the potential to enrich the body of knowledge for smart home technologies in a broader sense [4].

The previous research has mainly focused on the development of smart home systems that support specific tasks in a single home, like home surveillance or automatic light control [5], [6]. However, they do not integrate social network services to interact with other residents or the neighborhood and to exchange information with them via these systems, although it is suited for this context due to strong social component of living. Social network services in the information systems area are basically considered as a network of humans represented with a profile and their ability to connect with other profiles [7]. The establishment of such connections happens voluntarily between actors of the network [8]. Their motivation of doing so originates in self-representational or informational purposes [9], [10]. Furthermore, such network services offer a great possibility for individuals to claim their identity according to their self-perception [11], [12]. Additionally, they allow to extend the informational content of their user groups due to non-conformal behavior of individuals [13].

Imaginable scenarios for the development of smart homes integrating informational purposes of social network services are recommendation systems for food or entertainment that retrieves information from the social environment of the resident. A major obstacle in such a setting is the amount of data that is produced by such social networks and the effort that has to be conducted to analyze that data. But the progress in big data technologies in the recent years has enabled new possibilities. Therefore, the objective of this paper is to identify new research opportunities for smart home systems that integrate social network services and big data analytics to increase the ambient intelligence.

B. Methodology

To achieve our objective, an extensive literature review for smart home and big data was conducted. By making use of search engines like Google Scholar, Elsevier's ScienceDirect, IEEE Xplorer, AIS Electronic Library and the archives of the most important information systems journals, a first list of pertinent publications was created. After examining the list, a selection of the most relevant papers was compiled

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to determine the current state of research. Based on in these papers mentioned shortcomings, future works, and outlooks, possible research opportunities were developed and clustered into different categories [14].

The residual of the paper is organized as follows. It begins with an overview of big data with a focus on the associated analytical capabilities and a critical analysis of its challenges. Section 3 provides a definition and review of the smart home, highlighting its challenges. Following this, section 4 presents possible research opportunities for integrating social network services and big data into smart home systems. The last section concludes with a summary and outlook.

II. Big Data

This section aims to provide an overview of the big data topic. First, the term is defined and a classification of its different categories is presented, followed by a consideration of reference architecture. After that, the analytical capabilities that arise from big data are examined. At the end, the challenges associated with big data are discussed.

A. Definition and Characteristics

Since the term "big data" is ubiquitous nowadays and it has an ambiguous origin, many different definitions can be found in literature [15], [16]. However, [17] proposed the following definition based on a comprehensive literature review in the field of big data: "Big data is a set of techniques and technologies that require new forms of integration to uncover large hidden values from large databases that are diverse, complex, and of a massive scale" [17, 100]. Another prevailing possibility of defining big data is to describe it by its characteristics, which are called the Vs [17]. Originally, they contained only three characteristics: volume, variety, and velocity. Over time, researchers and industry extended the list by several additional attributes, such as value, veracity, variability, and complexity [15], [18]. However, the most widely used characteristics are the following ones:

Volume refers to the enormous amount of data that arises every second and continuously grows. The size of data exceeds the capabilities of traditional storage solutions and analysis techniques [15], [19], [17].

Variety refers to the heterogeneity of data that yields from different sources and various types of data. Data types are, for example, text, audio, video, pictures, sensor data or log data, which are in a structured or unstructured format. The challenge is to combine data sets with different formats and to analyze them together [15], [19], [17].

Velocity refers to the pace of the data generation, data flow and data analysis. Besides static data sets that are stored and processed later on, there are data streams that have to be continuously processed and analyzed in real-time without storing them [15], [19], [17].

Veracity refers to the quality of the captured data and its truthfulness. The information retrieved from a data set can only be as accurate and reliable as the source data. Forecast data, for instance, contains an inherent uncertainty that cannot be removed by the best cleansing technique. Therefore, the reliability of the data plays a crucial role in this context [15], [20].

Value refers to the value of the information that can be retrieved from the data. In general, big data exhibits a low value density. However, the volume of the data enables to exploit this potential and to discover meaningful and valuable information. [15], [19], [17].

B. Classification

According to the definition and its attributes, big data is characterized by diverse data sources and data formats. To get a better understanding of this heterogeneity, [17] provide a classification of the different categories. On the basis of the five aspects *data sources*, *content format*, *data stores*, *data staging*, and *data processing* they identified the specific characteristics of big data.

Relating to *data sources*, [17] distinguish between the categories web & social media, machine-generated data, sensing, transactions, and internet of things. Web & social media addresses the data that is generated by humans within online networks and communities, such as messages, posts or relationships between people provided by social network services. The tight interconnections between online social networks and big data, in particular its analytical techniques, can be summarized on the data level. Serving as data sources, essential information created by social network services are stored and retrieved by big data systems. They allow for multi-dimensional analyses of complex social networks, past and current information behavior of users as well as self-presentation trends among the network's participants. In contrast, machine-generated data is produced purely by computers without human interference (e.g. network logs). The third category is sensing that deals with the measurement of physical circumstances, like temperature or proximity. The next group represents all types of transactions. Their characteristic is that they have a time dimension for describing the events (e.g. financial data). Internet of things, the last category of data sources, addresses the set of physical objects that are connected to the internet, such as smartphones, medical devices or activity trackers. It goes without saying that there is no clear-cut border between these categories, but they provide a good orientation [17].

With regard to the *content format*, there are three different categories. The first one is the structured format. Data in this format exhibits a predefined data model, which predestines for relational databases. Due to their structure, it is easy to process and analyze data sets with such a format. Examples of this include customer databases or transactional data. The second category deals with semi-structured data. This data does not conform to a strict relational model, but it contains elements to distinguish between content and semantic and to describe the content, like XML documents. The less structured format aggravates the processing and analysis processes. However, it is less challenging than having unstructured data, like messages, images, or videos. In that case, the preprocessing steps need much more effort to transform the raw data to analyzable data [17].

Due to the volume and variety of data, there is no *data store* that meets all requirements of big data. Therefore, we can find several different database technologies used in the context of big data. The first is the column-oriented database, such as BigTable. They are similar to classical relational databases. However, they are optimized for enormous amounts of data and analytical computations. Another widely used technology is the key-value store. Since the data structure is limited to a key and a value, such databases exhibit a good scalability and are suited for high performance systems. To handle less structured data, document-oriented databases were developed. In comparison to relational databases, they provide a higher degree of flexibility regarding data models. A different approach is taken by graph databases, which use graph structures to store the data. Due to this concept, they are suitable to model relationships between arbitrary entities [17].

In terms of *data staging*, [17] identified three different categories. The first one covers the cleaning process that is needed to identify and correct inconsistencies and errors in the data. The next category addresses the transformation of data. Above all, semi-structured and unstructured data often need to be transformed to obtain an analyzable data set. The third and last category deals with the normalization, which is applied to reduce the redundancy and so to optimize the database [17].

Relating to *data processing* there are two ways data are processed in a big data scenario either batch or real-time. Batch processing is applied for complex and long-running jobs. Real-time processing is often used for stream data or ad-hoc analysis, but it is computation intensive and places high demands on the system [17].

C. Architecture

As we have learned in the previous sections, big data systems have to perform complex and sophisticated tasks. To cope with these challenges, such systems need an elaborate architecture. For that reason Pääkkönen and Pakkala developed a reference architecture based on "published implementation architectures of big data use cases" [21, 1].

Figure 1 illustrates the concept of the reference architecture. The rectangles represent functionalities, the ellipses data stores, and the arrows the data flow. The data principally flows from left to right. The part job and model specification is separated from the processing pipeline because it controls the pipeline rather than being part of the data flow.

The pipeline begins with the data sources, which are classified based on two dimensions in the architecture. Mobility, the first one, distinguishes between data that is not in motion (in situ) and streaming data. The second dimension is the structure of the data or the content format as it was defined in section 2.2. The second phase of the pipeline deals with the extraction of the data from the sources, followed by the storage of the data. After storing, the data is passed to the data processing phase. This step is necessary to prepare the data for the data analysis that is performed in the next phase. Subsequently, the results of the analysis pass the data loading and transformation phase to transform and store them in the system. The additional step is needed to prepare the data for presentation, which can be done in the form of visualization, dashboarding or other end user applications.

As mentioned above, this is only a reference architecture. That means that no big data system will exactly look like this because of the specific requirements needed for each. Nevertheless, such a reference model helps to design big data systems and to better understand the necessary processes, particularly because it is based on real big data architectures [21].

In the context of big data cloud computing plays a crucial role as an enabler and facilitator. First, it provides the required resources to perform the complex and sophisticated computations as an underlying engine. Second, it lowers the barriers to entry because it eliminates high investment and maintenance costs of dedicated hard- and software [17]. Thus, not only large companies that can afford the investment of their own big data infrastructure can use it, but also smaller companies and end consumers.

D. Big Data Analytics

Independent from its size, data by itself is worthless, unless hidden patterns, correlations, trends or other meaningful information are retrieved from the data. However, it demands an analytical process to turn raw data into useful insights. Related to big data, this can be particularly challenging. Volume and velocity aggravates the feasibility of data analysis because of technological limitations. Additionally, the variety of data types impairs the combination and linking of data from different sources. Therefore, advanced analytical methods and techniques are needed to process big data [15], [18]. Depending on the degree of intelligence, the literature distinguishes between three types of analytics, which are described as follows:

- *Descriptive Analytics* refers to the question what has happened and what is happening. It is the simplest form of analytics since it presents and explains events from the past and the present without making any predictions. Tools and methods in this context are business reports, ad-hoc reports, interactive reports, dashboard, and alerts the typical tools of business intelligence. The objective of descriptive analytics is to identify and

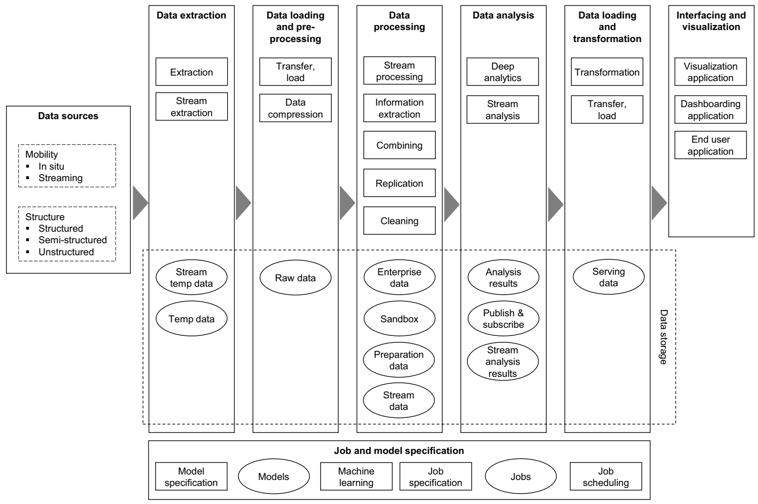

Figure 1. Reference architecture according to [21]

define business problems and opportunities [22], [23], [24].

- *Predictive Analytics* refers to question what could happen in the future. Instead of answering the question what was in the past, it uses the present and past data to predict the future. To reach meaningful results, analytical techniques with a higher degree of intelligence are required, such as simulations, predictive models, statistical forecasting methods, and other advanced data mining methods [22], [23], [24].
- *Prescriptive Analytics* refers to the question what should be done. It goes one step further than predicative analytics. While predictive analytics only tries to forecast the future, prescriptive analytics tries to maximize the future outcome by recommending the best course of actions. To achieve this, optimization, simulation or decision models are used, such as game theory or Monte Carlo Simulation [22], [23], [24].

Some researchers see an additional type between descriptive and predictive analytics, called diagnostic analytics [25], [18]. It deals with the reasons for why something happened. In the context of this paper, these aspects are seen as a part of the descriptive type.

Considering big data analytics from a data type perspective, it is possible to identify six analytical fields that play a crucial role in big data analytics. The first one is the structured data analysis, which analyzes, for instance, financial data or sensor data. Even if it was actively investigated and applied before the rise of big data, it is still an important topic due to the increasing masses of data [26], [19]. Another kind of analysis addresses text data. Since text is the prevailing format to store information, this field has a promising future. However, the extraction of meaningful information from unstructured data, e.g. documents or emails, is a sophisticated task [26], [19]. Similar challenges can be found in the multimedia data analysis. Due to the heterogeneity of multimedia data, like images, audio, and video files, the data extraction and the analysis are aggravated [19]. Besides that, web data analysis is an emerging research field. It deals with the discovery and extraction of knowledge from web services and documents [26], [19]. A closely related field in this context is the network analysis that refers to social networks, like Facebook, Twitter, and LinkedIn [26], [19]. The last field, the mobile data analysis, has arisen from the success of mobile devices. Mobile users generate a vast amount of data, such as text messages, geographical locations or other sensor data, which provides an enormous analytical potential [26], [19].

Summing up, analytics is the most challenging part in the processing of big data because it demand the highest degree of intelligence. However, it unlocks the value and transforms data in to useful information.

E. Challenges

Although big data is widely used in the industry and private sector, the technology is still in the early stages of development. There are many issues not fully addressed, while new challenges continue to arise. In this section, the major challenges are briefly discussed.

The diffusion of big data and the technological progress will induce the people to apply the technology to more complex and sophisticated data sets. The growing heterogeneity, the varying quality, and the diverse structures of the data will challenge all processing steps from extraction over transformation to analysis [20], [17].

Not only the data becomes more complex, but also the computations. The algorithms have to handle increasing amounts of data with growing complexity. To ensure efficiency and scalability of the systems, it is necessary to develop new algorithms and concepts. Promising examples of approaches are distributed algorithms and the usage of cloud computing to share computing capacities [20], [17].

With the increase of the data and computational complexity, the systems will become more complex. Therefore, the development of system architectures, computational frameworks, and processing solutions is necessary to satisfy the prospective requirements of big data, which emerge from the previously mentioned challenges. In this context, energy efficiency has also to be taken into account to ensure the operational efficiency of the systems [20], [17].

In addition, research on big data faces security and privacy challenges. The gathered data sets might contain either personal information or business secrets. Therefore, the protection of the data is indispensable to prevent abuse. Relating to cloud computing, the problem is further exacerbated because the data is outsourced to external data centers. Consequently, security and privacy remain ongoing challenges [17].

A less technical challenge emerges from legal and regulatory issues. On the one hand, legal requirements can contribute to data security and privacy. On the other hand, they can impair the diffusion of big data. For instance, they can prohibit the analysis of specific data, like personal data. Another possible issue results from conflicting jurisdictions that arise, if data storing and processing are outsourced to another state or country. Therefore, it is a challenge to create a convenient legal foundation for big data [17].

III. Smart Home

This section aims to provide an overview of smart homes and the current state of research. The definition of smart home is followed by a classification, an overview of contributing technologies, and the challenges of smart homes.

A. Definition

Similar to big data, many different definitions for smart home can be found in literature [5]. Such a variety can be ascribed to the fact that the concept of the smart home is relatively old and the progress continuously expanded the technical possibilities in this area [1]. Given the current state of research, a smart home can be defined "as an application of ubiquitous computing that is able to provide user context-aware automated or assistive services in the form of ambient intelligence, remote home control, or home automation" [5, 1191].

B. Classifications

To get an overview of the smart home topic, it makes sense to consider the different types and application areas. Therefore, two different classifications are outlined in this section. The first one, which was proposed by [27], distinguishes between five types of smart homes based on their degree of intelligence:

1) *Home which contains intelligent objects*: That means that there are appliances and objects that exhibit an intelligent behavior, but that do not interact, e.g. an intelligent thermostat that automatically controls the room temperature [27, 34].
2) *Home which contains intelligent, communicating objects*: In contrast to the previous type, the intelligent objects and appliances are able to communicate and exchange information, e.g. a set of connected thermostats that interact to reduce heating costs [27, 35].
3) *Connected home*: By integrating internal and external networks, information and services of the home can be accessed and controlled either by remote or within the home [27, 35].
4) *Learning home*: The home records the activity of the appliances and objects to retrieve patterns from the accumulated data. The discovered patterns serve as basis to predict residents needs and to control the home [27, 35].
5) *Attentive home*: The home constantly registers the activity of its residents and objects to extract behavioral patterns. This information is used to anticipate the residents needs and to control the home [27, 35].

Besides the classification according to the degree of intelligence, it is useful to differentiate between the various application areas of smart homes. Unfortunately, the literature provides several different categorizations for this topic. Therefore, a new classification was derived from four reviews of smart home research, as shown in table I. We explored the application domains used in the identified papers and grouped them in mutually exclusive categories. Thus, we were able to summarize them in five comprehensive groups on which we will elaborate in the remainder of this paper.

C. Contributing Technologies

According to [29], the technologies from the following areas are needed to make a home more intelligent: *sensing*, *reasoning*, *acting*, *human-computer interaction* (HCI), *security and privacy*.

Since a smart home system exhibits a high degree of interaction with the real world, sensors are an elementary part used to perceive the state of the physical environment. They provide the system with data regarding the status of the home, its objects, and its residents. Over time, a variety of different sensor types for the domestic usage has been developed, such as sensors that collect environmental parameters, gather status information of the home and its objects, or determine the resident's location or his health status [5], [1].

In order to transform the data provided by sensors to meaningful information, a *reasoning* component is required. The first level of *reasoning* is to determine the resident's activity based on the sensor data. Often a combination of different sensors is used to increase the accuracy. After

Application Area	Description	Alam et al., 2012 [5]	Badica et al., 2013 [3]	De Silva et al., 2012 [28]	Solaimani et al., 2011 [2]
Assisted Living	Eldercare, childcare, and home care		•	•	•
Comfort and Convenience	Home automation, remote access, digital assistant, recommender system, and shopping	•	•	•	•
Communication and Entertainment	Communication and entertainment systems, social networks		•		•
Energy Management	Monitoring and controlling of energy consumption, smart grids		•	•	•
Healthcare	Monitoring of health status	•		•	•
Security	Home security and surveillance	•	•	•	•

Table I
APPLICATION AREAS OF SMART HOME

determining the activity, the next step is to predict the resident's behavior and to make decisions [1], [29].

With these two technologies, a smart home system is only able to perceive the environment. However, it must be able to act in order to provide additional value for the residents. Therefore, a technology that manages the autonomously *acting* is necessary [1], [29].

The goal of a smart home is to make living more comfortable. On the one hand, this means that the system should act as autonomously as possible with minimal interaction between the resident and the computer. On the other hand, there are many situations in which the resident must interact with the system. Consequently, *HCI* is an elementary success factor that has to be regarded during the development. A challenge in this context is that such systems have a broad range of users with different skills and characteristics, e.g. children, teenagers or the elderly. Therefore, the interaction methods should be as intuitive and natural as possible, like speech- and gesture-based control. Besides that, the usability can be increased by the context-awareness of the system. This reduces the amount of information that has to be input by the user [1], [29].

The fifth contributing technology addresses the topics of *security and privacy*. Since smart home systems are deeply integrated into the residents' private lives and private information is shared with them, such systems have to be able to protect themselves and the stored data from external attacks [1], [29]. Additionally, these aspects influence the willingness to use the technology, because the users are aware of the potential threats [1].

D. Challenges

The continued progress in ubiquitous and pervasive computing has facilitated the research in the field of smart homes. In the previous years, more and more products emerged from these results and came into the market. Nevertheless, there are still challenges that must be addressed to drive the development of smart homes forward and to increase the ambient intelligence [6].

One critical aspect is the efficiency and reliability of the sensor systems and the processing algorithms. Despite the variety of available sensors and processing software, the accuracy of the results exhibits potential for improvement [6], [5].

Besides that, the standardization of smart home systems has to be actively fostered. At the moment, several different technologies are on the market that are not able to interact. However, this lack of intercompatibility impairs the users' acceptance and consequently the market diffusion of such systems [6], [5].

Another set of challenges results from the necessity of security and privacy, which has already been mentioned in the previous section. Since the users share private data with the systems, particularly in the context of healthcare, it must be ensured that the data is stored safely and is protected from unauthorized access. This does not only refers to technical aspects, but also legal and ethical ones [6], [5], [29].

In terms of assisted living and healthcare, the aspects of legal issues, cost effectiveness, and reimbursement will play a crucial role in the future. The first one arises from the uncertain legal situation in the field of telemedicine. The other two aspects refer to the high investment and maintenance costs of the medical equipment. However, a reimbursement from insurance companies, for example, could facilitate the diffusion of assisted living and consequently decrease the costs in the long run [6].

Finally, the success of smart homes strongly depends on the services and functionalities that they provide their residents. Therefore, a major challenge is to develop solutions that are accepted by the users and that satisfy the users' needs. Otherwise, smart homes are doomed to failure [6], [5]. For that reason, social network services play a major role in designing and developing smart home technology, as they emphasize their users as well as their connectedness. They created a culture of easy interaction and, by that, set free a huge business and use potential for smart home technology through vast content creation and consumption [4].

IV. Research Opportunities

After considering big data and smart homes independently from each other, we discuss in this section possible research opportunities arising from integrating social network services and big data analytics into smart home systems. The underlying questions are how ambient intelligence can benefit from social networks and big data and what challenges need to be addressed for its success. Until now, this research field has been minimally investigated [30]. However, [26], [19], and [30] ascribe a huge potential to it or to its sub fields. Therefore, the research opportunities are mainly derived from the literature reviews of smart homes and big data. The results are categorized into five perspectives. The first one deals with new business models, followed by the behavioral perspective that addresses the user acceptance. After that, the human-computer interaction and technology area are covered. Finally, analytical research topics are suggested in the terms of smart homes and big data. The list of opportunities does not claim to be complete. It rather proposes relevant research topics.

A. Business Perspective

According to [31], ”big data enables companies to create new products and services, enhance existing ones, and invent entirely new business models” [31, 5]. That also applies to the combination of smart homes with big data analytics and social network services . As previously indicated, online social networks provide a tremendous amount of information as data source, like the created content, established connections as well as continuously ongoing interaction. Due to the complexity and resource demand of big data infrastructure such solutions cannot be completely operated at home. Some parts have to be outsourced to data centers because of costs and convenience. This shift transforms hard- and software providers to service providers, creating opportunities for new business models. Not only can services be monetized, but also the highly personalized data that are gathered by the systems. Due to the social networking component, the data also covers relationships between residents and neighbors and it is not only limited to an individual, increasing the value of the data. Even the analysis of social network data combined with the sensor data of smart homes requires the application of big data techniques for providing meaningful results. Furthermore, it is conceivable to integrate other companies as co-financiers [30]. An insurance company, for instance, could bear a part of the costs for assisted living to avoid higher costs through a permanent stay in a retirement home. A good starting point for the development of business models is provided by [32]. They proposed a framework for aligning business models related to smart home services. Beyond that, existing cloud computing business models from other industries can be used for guidance.

B. Behavioral Perspective

Another set of research opportunities deals with the behavioral aspects of technology. A technology is successful, only if it is accepted by its users and if it is used. Therefore, it is necessary to identify social barriers and other factors that the actual system use depends upon [33]. With these insights, it is possible to develop technology that satisfies the users’ needs. An empirical study that addresses this topic in the context of smart homes was published by [34]. They investigated the user acceptance of smart products based on the Unified Theory of Acceptance and Use of Technology (UTAUT). However, they only considered smart products in a kitchen environment and did not integrate any social network or big data issues. Thus, the study would be a good basis for further research in the field of smart homes supported by online social networks and big data analytics; though the scope should be extended to all application areas and aspects of social networks as well as big data have to be incorporated. Most importantly, the latter might influence the results. The existing security and privacy concerns of smart home systems [1] could be exacerbated by social network services and big data, consequently impairing the user acceptance of such systems. The research opportunities are not limited to the UTAUT model in this perspective. It rather offers a solid starting point. Nevertheless, other models or modification of the UTAUT model should be considered because it originally emerged in an industrial domain and not a private domain [34].

C. Interaction Perspective

According to [35], the human-computer interaction strongly contributes to the success of smart homes. The systems are supposed to assist their users in their daily routines. Consequently, the interaction between the user and the systems should be as easy and effortless as possible to foster their usage and to avoid complications. This implies the necessity of developing intuitive and simple interfaces. However, the integration of social network functionalities and big data analytics can increase the complexity of the systems and this can affect the user interfaces. Due to this, it would be interesting to investigate how the potential can be made accessible whilst ensuring a high degree of usability. To obtain meaningful results, it is necessary to involve the subsequent users in the design process [36]. Besides the human and technology relationship, the relationships between technology and home and between human and home have to be involved in the research [37]. Furthermore, the relationship between human and human that arises from the interaction in social networks has to be investigated, as well. Social networks are also a helpful tool for evaluating designed interaction interfaces with smart home technology or the user's satisfaction. The created content in such networks can be analyzed through big data.

D. Technological Perspective

It was already mentioned that the security and privacy of the data are critical aspects influencing the acceptance of smart homes [1], [29]. Above all else, storing and sharing data with external service providers relating to cloud computing might exacerbate this difficulty. To counteract this, it is conceivable to anonymize the data before it leaves the smart home system. A first approach is proposed by [38] who uses k-anonymization to protect medical data. Nevertheless, this topic requires further research to become applicable. Besides that, the user should have the possibility to define which data he or she wants to share within the a social network or to include from other social peers. Since data collected at home has a strong personal and private character.

E. Analytical Perspective

The last perspective deals with possible analytical research topics, which are enabled by the integration of social network components and big data analytics into smart homes.

Relating to assisted living, the integration of big data technologies might improve the recognition, tracking, and prediction of residents' activities. Due to the computational power and the possibility to process large data amounts from different sources, the accuracy and reliability of the systems might be improved. Besides that, a recommendation system is imaginable that suggests elderly activities to facilitate their mental and physical fitness. This is beneficial because insufficient activity impairs the health, particularly in old age [39]. Social networks can assist in such situations, as they would facilitate communication among closest peers that should be notified in case of unusual habits or potentially dangerous circumstances. It would fulfill the information needs of connected users that care.

With reference to comfort and convenience, social networks and big data can contribute to the identification of behavioral patterns and the prediction of the next activities. An improved reliability would increase the context-awareness of smart homes and consequently the degree of convenience. A possibly interesting topic is a system recommending a shopping list based on the current inventory, residents' eating habits, and external data, such as seasonal aspects and advertisement. Due to the sharing of information through social networks, it could be easier to identify patterns and trends so that the prediction is more reliable.

Similar to the previous area, the communication and entertainment area might benefit from the improvements in determining behavioral patterns and forecasting next activities to enhance the user experience. Hereby, information collection within social networks and their analysis with big data techniques is highly promising [4]. Facebook likes of a resident or of his or her friends, for example, might a good indication for his or her preferences. Such information can be used to develop a cross-platform recommender system for entertainment activities, such as music, movies, TV shows, and video games. The concept is similar to movie recommender system, like the one for the streaming platform Netflix [40]. However, it relies on much more data sources than just the users' preferences and is not limited to one platform. Social networks are a valuable data pool for this purpose.

In regard to the energy management area, online social networks comprise the ability to supply either consumers or energy providers with valuable information by including smart home devices. On one hand, they could increase the residents' awareness of usage and consequently reduce the energy consumption. Furthermore, the prediction of energy consumption could be improved by more sophisticated models and the integration of external data, such as weather or pricing data. In a future step, these results could be used for simulations that determine optimal appliance schedules, e.g. for washing machines or air conditioning systems. For the last two aspects, it is worth considering the creation of a social network between many thousands of households. On the other hand, the social network would increase the accuracy of the forecasts and so give suppliers the opportunity of optimized energy consumption forecasts.

Concerning healthcare in smart homes, the integration of social networks and usage of big data analytics might advance the monitoring of the fitness and state of health. Besides that, predictive analytics allows recognition of abnormalities in order to prevent diseases and to reduce treatment costs. Although this topic is currently being investigated [41], [42], [43], it contains a huge potential for further research. Regarding the prescriptive analytics, the results from the other types, for instance, can be used to develop automated notification systems or a recommendation system for food and activities that is based on the resident's habits and state of health. In regard to social networks, it is critical to share such information with other people. But using a social network to share fitness information, as it is provided by many sports apps, would the imaginable in a smart home environment. Additionally, similar to assisted living, close peers of the network or even nursing personnel can be notified when certain conditions are fulfilled.

Furthermore, the design of smart homes by integrating social network services and big data analytics can profit from reliability improvements of home security systems. The integration of predictive policing and a network between neighboring households are conceivable to predict possible incursions and to inform the neighborhood. Depending on the reliability of the system, it would be possible to inform the absent residents or neighbors or make automated emergency calls. To prevent incursions, a smart home might imitate activity in the house based on the learned behavioral patterns of its residents. Thus, possible burglars would be scared off.

V. Conclusion

The integration of online social networks and big data analytics into the design of smart home systems has been less investigated when compared to each individual field. However, that does not imply that there is no demand for research. On the contrary, it contains a huge potential for such research. In this paper we identify and address five different perspectives that provide a wide range of possible research opportunities in the field. The proposed list does not claim to be complete. But it provides a good starting point for future research.

One of the most crucial aspects that must be addressed is the topic of security and privacy. Smart home systems have a deep insight in our private lives and we share a wealth of personal data with them, even on social networks already. The users are aware of these aspects and willing to accept them. It will become critical however, if another technology with privacy and security concerns, such as big data or social networks, is integrated in these systems. Therefore, this topic has to be considered in order not to scare potential users off. In this context, it is also important to be transparent and to always give the user the feeling of having control over the system. Concerning the analytical perspective, the application areas of comfort and convenience and communication and entertainment seem to be promising. Due to the integration of social networks and the analysis of the data with the aid of big data techniques, the reliability of prediction and trends shall be improved. For instance, predicting of a single person's shopping behavior would take some time until the system has collected enough information. But if the system is able to use data from his or her social environment combined with information of the smart home, it could be faster and it might discover trends. Other meaningful analytical research opportunities can be found in assisted living. Since we live in an aging society and elderly care becomes a more and more important topic, the integration of social networks and big data might facilitate assisted living. Due to the new capabilities, elderly people are supported in their daily routines and consequently can longer live independently. Social networks, for example, can help to communicate with family members or care attendants. Besides the challenges and opportunities arising from the combination of the research fields, the challenges of each single field do not have to be neglected because they form the foundation.

If all these challenges are addressed, the future of smart homes looks promising. Through the integration of online social networks and big data analytics, we will be able to build smart homes that provide us with a much higher degree of comfort and convenience than before.

References

[1] K. Rasch, "Smart assistants for smart homes," Dissertation, KTH Royal Institute of Technology, 2013.

[2] S. Solaimani, H. Bouwman, and N. Baken, "The smart home landscape: a qualitative meta-analysis," in *Toward Useful Services for Elderly and People with Disabilities*. Springer, 2011, pp. 192–199.

[3] C. Badica, M. Brezovan, and A. Badica, "An overview of smart home environments: Architectures, technologies and applications," in *Proceedings of the 6th Balkan Conference in Informatics*. ACM, 2013, pp. 179–186.

[4] M. Chui, J. Manyika, J. Bughin, R. Dobbs, C. Roxburgh, H. Sarrazin, G. Sands, and M. Westergren, "The social economy: Unlocking value and productivity through social technologies," *McKinsey Global Institute*, no. July, pp. 1–18, 2012.

[5] M. R. Alam, M. B. I. Reaz, and M. A. M. Ali, "A review of smart homes - past, present, and future," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, vol. 42, no. 6, pp. 1190–1203, 2012.

[6] M. Chan, D. Estève, C. Escriba, and E. Campo, "A review of smart homes - present state and future challenges," *Computer methods and programs in biomedicine*, vol. 91, no. 1, pp. 55–81, 2008.

[7] D. Boyd and N. Ellison, "Social network sites: definition, history, and scholarship," *IEEE Engineering Management Review*, vol. 3, no. 38, pp. 16–31, 2010.

[8] H. Krasnova, S. Spiekermann, K. Koroleva, and T. Hildebrand, "Online social networks: why we disclose," *Journal of Information Technology*, vol. 25, no. 2, pp. 109–125, 2010.

[9] C. M. Cheung, P.-Y. Chiu, and M. K. Lee, "Online social networks: why do students use facebook?" *Computers in Human Behavior*, vol. 27, no. 4, pp. 1337–1343, 2011.

[10] A. Nadkarni and S. G. Hofmann, "Why do people use facebook?" *Personality and individual differences*, vol. 52, no. 3, pp. 243–249, 2012.

[11] J. H. Kim, M.-S. Kim, and Y. Nam, "An analysis of self-construals, motivations, facebook use, and user satisfaction," *Intl. Journal of Human–Computer Interaction*, vol. 26, no. 11-12, pp. 1077–1099, 2010.

[12] S. Zhao, S. Grasmuck, and J. Martin, "Identity construction on facebook: Digital empowerment in anchored relationships," *Computers in human behavior*, vol. 24, no. 5, pp. 1816–1836, 2008.

[13] T. Neben and D. Lips, "Breaking the norm - on the determinants of informational nonconformity in online social networks," in *19th Americas Conference on Information Systems, AMCIS 2013, Chicago, Illinois, USA, August 15-17, 2013*, 2013.

[14] J. Webster and R. T. Watson, "Analyzing the past to prepare for the future: Writing a literature review," *Management Information Systems Quarterly*, vol. 26, no. 2, p. 3, 2002.

[15] A. Gandomi and M. Haider, "Beyond the hype: Big data concepts, methods, and analytics," *International Journal of Information Management*, vol. 35, no. 2, pp. 137–144, 2015.

[16] F. X. Diebold, X. Cheng, S. Diebold, D. Foster, M. Halperin, S. Lohr, J. Mashey, T. Nickolas, M. Pai, M. Pospiech *et al.*, "A personal perspective on the origin (s) and development of big data: The phenomenon, the term, and the discipline," 2012.

[17] I. A. T. Hashem, I. Yaqoob, N. B. Anuar, S. Mokhtar, A. Gani, and S. U. Khan, "The rise of big data on cloud computing: Review and open research issues," *Information Systems*, vol. 47, pp. 98–115, 2015.

[18] G. Shen, "Big Data Analytics And Technologies," *RDIAS Journal of Information Technology and Computer Applications*, vol. 1, no. 1, pp. 1–6, 2013.

[19] M. Chen, S. Mao, and Y. Liu, "Big data: A survey," *Mobile Networks and Applications*, vol. 19, no. 2, pp. 171–209, 2014.

[20] X. Jin, B. W. Wah, X. Cheng, and Y. Wang, "Significance and challenges of big data research," *Big Data Research*, 2015.

[21] P. Pääkkönen and D. Pakkala, "Reference architecture and classification of technologies, products and services for big data systems," *Big Data Research*, 2015.

[22] D. Delen and H. Demirkan, "Data, information and analytics as services," *Decision Support Systems*, vol. 55, no. 1, pp. 359–363, 2013.

[23] J. R. Evans, "Business analytics: the next frontier for decision sciences," *Decision Line*, vol. 43, no. 2, pp. 4–6, 2012.

[24] D. J. Power, "Using big data for analytics and decision support," *Journal of Decision Systems*, vol. 23, no. 2, pp. 222–228, 2014.

[25] A. Banerjee, T. Bandyopadhyay, and P. Acharya, "Data analytics: Hyped up aspirations or true potential?" *Vikalpa*, vol. 30, no. 4, pp. 1–11, 2013.

[26] H. Chen, R. H. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact." *Management Information Systems Quarterly*, vol. 36, no. 4, pp. 1165–1188, 2012.

[27] F. K. Aldrich, "Smart homes: past, present and future," in *Inside the smart home*. Springer, 2003, pp. 17–39.

[28] L. C. De Silva, C. Morikawa, and I. M. Petra, "State of the art of smart homes," *Engineering Applications of Artificial Intelligence*, vol. 25, no. 7, pp. 1313–1321, 2012.

[29] D. J. Cook, J. C. Augusto, and V. R. Jakkula, "Ambient intelligence: Technologies, applications, and opportunities," *Pervasive and Mobile Computing*, vol. 5, no. 4, pp. 277–298, 2009.

[30] V. Vimarlund and S. Wass, "Big data, smart homes and ambient assisted living." *Yearbook of Medical Informatics*, vol. 9, pp. 143–9, 2014.

[31] J. Manyika, M. Chui, B. Brown, J. Bughin, R. Dobbs, C. Roxburgh, A. H. Byers, and M. G. Institute, "Big data: The next frontier for innovation, competition, and productivity," 2011.

[32] S. Solaimani, H. Bouwman, and M. De Reuver, "Smart home: aligning business models and providers processes; a case survey," in *Proceedings of the 21st Australasian Conference on Information Systems (ACIM), Brisbane*, 2010.

[33] N. Balta-Ozkan, R. Davidson, M. Bicket, and L. Whitmarsh, "Social barriers to the adoption of smart homes," *Energy Policy*, vol. 63, pp. 363–374, 2013.

[34] P. Mayer, D. Volland, F. Thiesse, and E. Fleisch, "User acceptance of 'smart products': An empirical investigation." in *Wirtschaftsinformatik*, 2011, p. 9.

[35] G. Leitner, M. Hitz, A. Fercher, and J. Brown, "Aspekte der human computer interaction im smart home," *HMD Praxis der Wirtschaftsinformatik*, vol. 50, no. 6, pp. 37–47, 2013.

[36] C. Röcker, "User-Centered Design of Intelligent Environments: Requirements for Designing Successful Ambient Assisted Living Systems," in *Proceedings of the Central European Conference of Information and Intelligent Systems (CECIIS'13)*, 2013, pp. 4–11.

[37] T. Saizmaa and H.-C. Kim, "A holistic understanding of hci perspectives on smart home," in *Networked Computing and Advanced Information Management, 2008. NCM'08. Fourth International Conference on*, vol. 2. IEEE, 2008, pp. 59–65.

[38] A. Chakravorty, T. W. Wlodarczyk, and C. Rong, "A scalable k-anonymization solution for preserving privacy in an aging-in-place welfare intercloud," in *Cloud Engineering (IC2E), 2014 IEEE International Conference on*. IEEE, 2014, pp. 424–431.

[39] B. Elsawy and K. E. Higgins, "Physical activity guidelines for older adults," *American family physician*, vol. 81, no. 1, pp. 55–9, 2010.

[40] G. Arora, A. Kumar, G. S. Devre, and A. Ghumare, "Movie recommandation system based on users' similarity," *International Journal of Computer Science and Mobile Computing*, vol. 3, no. 4, pp. 765–770, 2014.

[41] P. Rashidi and D. J. Cook, "Com: A method for mining and monitoring human activity patterns in home-based health monitoring systems," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 4, no. 4, p. 64, 2013.

[42] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, "Automated cognitive health assessment using smart home monitoring of complex tasks," *Systems, Man, and Cybernetics: Systems, IEEE Transactions on*, vol. 43, no. 6, pp. 1302–1313, 2013.

[43] A. Salih and A. Abraham, "A review of ambient intelligence assisted healthcare monitoring," *International Journal of Computer Information Systems and Industrial Management (IJCISIM)*, vol. 5, pp. 741–750, 2013.