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Review

A Review of Smart House Analysis Methods for Assisting Older People Living Alone

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Abstract: Smart Houses are a prominent field of research referring to environments adapted to assist people in their everyday life. Older people and people with disabilities would benefit the most from the use of Smart Houses because they provide the opportunity for them to stay in their home for as long as possible. In this review, the developments achieved in the field of Smart Houses for the last 16 years are described. The concept of Smart Houses, the most used analysis methods, and current challenges in Smart Houses are presented. A brief introduction of the analysis methods is given, and their implementation is also reported.

Keywords: smart environment; assisted living; user activity recognition; user behaviour modelling; pattern recognition; challenges; limitations

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1. Introduction

The concept of the "Smart House" is generally used to refer to any environment designed to help people in their everyday activities in order to promote an independent lifestyle [1–3]. Smart Houses, in this context, are designed for any person, regardless of whether they have a disability or not. These Smart Houses include sensors and actuators to supervise the house environment and sometimes the occupant, to communicate with other devices, and to support or assist the occupant in their daily activities [4].

The Smart House concept is specially regarded as a promising path to improve access to home care for the older and people with disabilities. Smart Houses offer the opportunity to support older adults who wish to live in their own home for as long as they can care for themselves [1,5].

Furthermore, Smart Houses could also help older adults living with cognitive disabilities (including Alzheimer's or any other type of dementia) who have difficulty completing "activities of daily living" (ADLs: eating, toileting, bathing and dressing) [5,6].

Older people with cognitive disabilities are normally aided by caregivers, family members or professionals, who supervise the older adult's activities and guide them when necessary. For the older adult, the dependency on a caregiver may lead to frustration, anger and helplessness in particular situations, such as using the bathroom [6]. In addition, "a person's control of his/her personal space is an important component of human dignity and the quality of life" [7].

According to Statistics Norway's figures from 2017 [8], where the authors are conducting the research, people aged 67–79 years represent 10.4% of the population, and the oldest, 80 years and over, represent 4.2%. Moreover, by 2060, the group aged 70 and over will increase to around 19% [8]. This increment in the older population is also taking place in the majority of European countries, China, United States and Japan [1]. In addition, this trend will continue to increase over the years as shown in Figure 1.

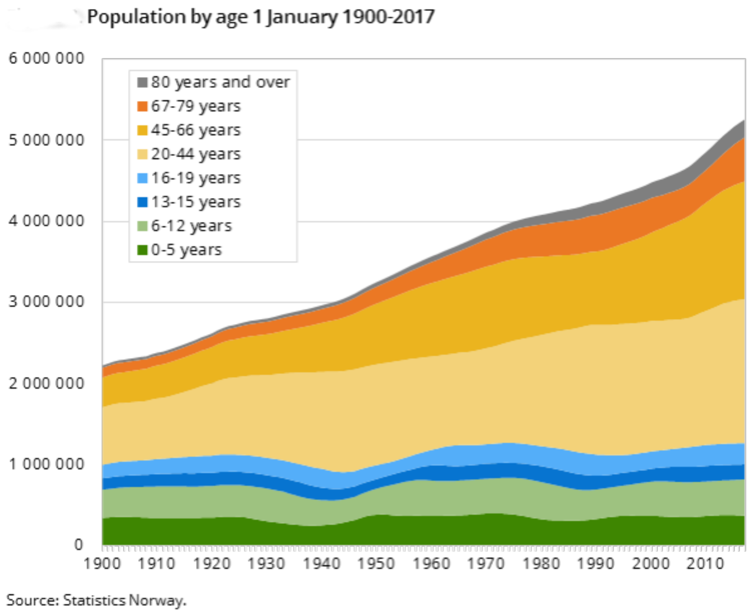

Figure 1. Statistics Norway [8].

Nursing homes will not be able to accommodate every individual aged 80 or over. Therefore, increasing the length of time that an individual can remain in their own home is both economically valuable and beneficial for most users [9]. In several cases, the government, social service organizations, and even individuals and families are turning to technological solutions to aid care giving for the growing elderly population [4].

Previous reviews have been conducted in the field of Smart Houses [1,10–13]. However, in this article, a systematic literature review is reported to show the developments achieved in the last 16 years on the emerging field of Smart House technology. The emphasis is on the analysis methods for predicting human activity and behaviour modelling, since this is the main focus for the further research of the authors.

2. Research Methodology

2.1. Aim

The aim of this review is to describe the most common analysis methods used for human activity and behaviour recognition in Smart Houses, as well as the main challenges of developing it.

2.2. Design

This review was conducted as a literature review based on the guidelines proposed by Kitchenham [14], and following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram [15].

2.3. Research Question

The research questions addressed by this study are:

- Q1. What are Smart Houses?
- Q2. What is the history of the Smart House?
- Q3. What the technology devices are used in a Smart House environment?
- Q4. What analysis methods or algorithms have been implemented in a Smart House environment?
- Q5. What are the current challenges involved in deploying a Smart House?

Regarding Q1., a subquestion was formulated to give a full insight into what a Smart House is: Q1.1 What are the concepts of a Smart House? Q2., aimed at ascertaining how Smart Houses have evolved. Q3., was answered by investigating what are the typical devices and sensors used in a Smart House, and how these devices are used. Q4. was addressed by summarizing the most common used algorithms or analysis methods in a Smart House system, including the advantages and disadvantages.

Finally, Q5 was also divided into subquestions:

- Q5.1 What are the technological challenges?
- Q5.2 What are the ethical challenges?
- Q5.3 What are the legal challenges?

2.4. Search Process

This review of literature was conducted through an initial search of the following databases: ACM Library, ScienceDirect, IEEE, Academic Search Premier (EBSCO), and SCOPUS. A manual search was performed in these databases and the relevant papers found were selected. The period of search in these databases was from May 2016 to August 2016.

All papers containing the terms "smart house" or "smart home" or "welfare technology" or "assisted living", "user behaviour" or "user behavior", "pattern recognition" "elderly" or "aged" or "older adult", and "algorithm" or "analysis method", as main subject headings, abstract and/or keyword were identified. A total of 4028 articles were found.

In addition, a second search was done to find seminal articles as a basis for the analysis or algorithm methods used within the Smart House technology. This search resulted in 25 conceptual articles, including books and article sources.

A third search was performed to find the legal and ethical challenges, however, this search was not performed as systematically as the main search. Thus, 4 articles on legal challenges and 6 articles on ethical challenges were added to this review. Finally, 13 articles were added by expert source recommendation.

Details on the search process and outcome can be found in Appendix A.

2.5. Selection Criteria

The literature search identified 4028 references as shown in Figure 2.

The following papers were included:

- Literature reviews on Smart Houses.
- Articles including assessment of projects (such as Smart House or assisted living).
- Articles focusing on Smart Houses for adults or older adults.
- Analysis or algorithm methods used in Smart House environments.
- Surveys describing user satisfaction with Smart Houses or the devices used in Smart Houses.
- Articles focusing on Smart Houses or environments adapted to the user.
- Articles about the challenges of implementing a Smart House.
- Articles from 2000 to present.

The following papers were excluded:

- Articles focusing on child welfare.
- Articles focusing on energy or bill reduction in a Smart House environment.
- Non-English language articles.
- Duplicates.

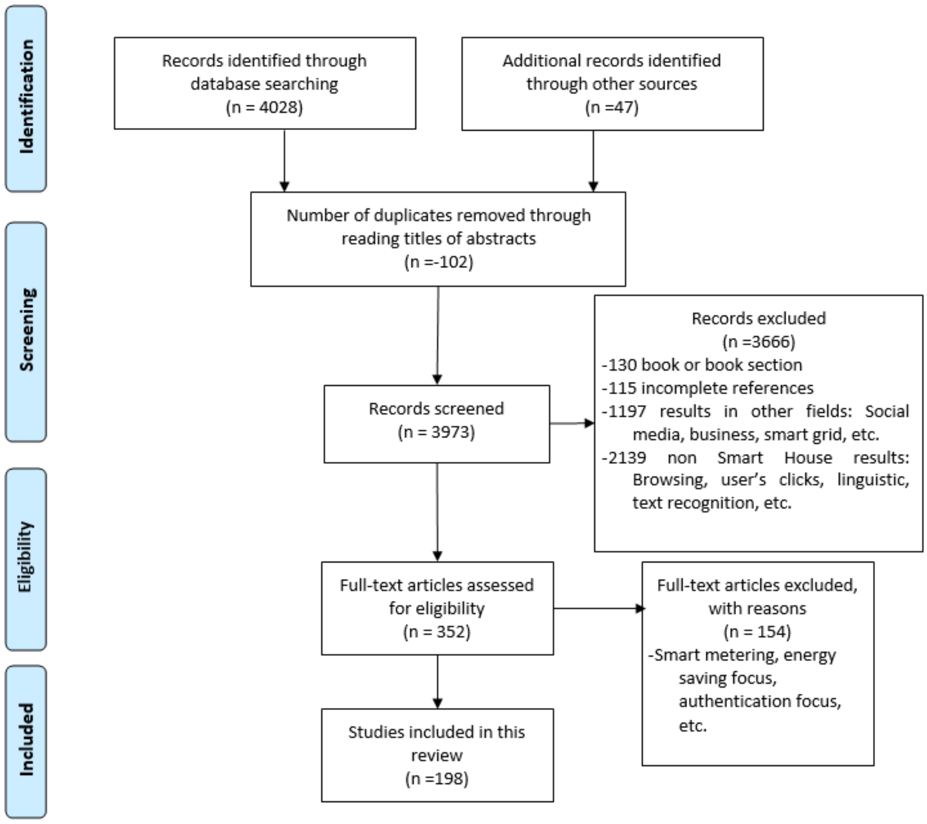

Figure 2. Database Search.

2.6. Search Outcome

A total of 4028 records were identified through database searching and 47 additional records were identified through other sources. See Appendix A for more details on the search outcome.

Of 4028 articles found, 102 articles were duplicates and removed. A total of 3723 articles were rejected during initial screening: 130 or being a book section or book reference, 115 due to incomplete references (missing author or journal name), 168 because of year range, 1197 for reporting user behaviour recognition in different areas (social media, education, business, shopping, etc.), 2139 due to not having results in Smart House or Smart Home for older adults. The remaining 305 articles were reviewed in full-text and 154 articles did not meet the selection criteria and were excluded. A total of 198 articles meeting the selection criteria and quality assessment were included in this review.

2.7. Data Synthesis

The data found while following this methodology was organized in clusters to report the main results on Smart House Welfare Technology. The clusters include: Smart House concepts, history of Smart Houses, technology devices (sensors), analysis methods (software and algorithms), challenges and concerns including: technological, ethical and legal challenges.

3. Results

3.1. Smart Houses

The concept of Smart House welfare technology has been under development for several decades now. Smart Houses, in this setting, are a hopeful and cost-effective path improving access to home care for the older population and disabled [1,13,16]. Several universities and research project groups have developed Smart House prototypes or single devices to be adapted in Smart Houses. These Smart Houses are mainly developed to supervise older adults with any disabilities such as "motor, visual, auditory or cognitive" [1].

3.1.1. User Activity and Behaviour

People tend to follow specific patterns in their daily lifestyle. In a Smart House context, the user's daily activities generate patterns that play an important role in predicting future events in the Smart House [17,18]. The goal of a Smart House environment is to assist the user with their daily life activities; thus, the Smart House should find repetitive patterns in the user's activities and predict the behaviour of the user for additional assistance [19,20].

User activity monitoring is employed to observe and record the actions of the person, with a view to achieving the "goals of comfort and efficiency" that a Smart House can offer [21]. User behaviour refers to the range of actions, conduct and responses made by the user. Therefore, the Smart House needs to be capable of learning and applying the knowledge acquired in order to adapt the house to the user's behaviour [22,23]. Because the user generates a pattern, abnormal user behaviour can be exposed by the construction of the user's normal behavioural pattern [18].

Generally, sensors and cameras in a Smart House are used to track or identify the user's activities and perform human behaviour analysis [24]. The user's behaviour can be used to predict and determine future user trends. Thus, the activity recognition method implemented by Smart Houses should be as accurate as possible in order to control the system. The activity recognized by the method "can provide the appropriate service to the user automatically" [18].

Artificial intelligence algorithms, machine learning algorithms, and data mining techniques are used to model and predict the user's behaviour. These algorithms and techniques include, but are not limited to Bayesian Method, Markov Chain, statistical inferential algorithms, neural networks, Fuzzy logic and Multiagent System (MAS) among others [17,19].

More details about the algorithms and techniques used for user activity and behaviour learning and monitoring are described in Section 3.4.

3.1.2. Context Awareness

Context awareness is an important step in the user activity and behaviour concept. Context "is the key for interaction without distraction" [25,26]. Brdiczka et al. [26] stated that "context describes features of the environment" where the activity takes place. The role of a context-aware house is that the system builds and stores a model describing the environments and the occupants' activities and behaviour.

Schilit et al. [27] refer to context as location: where you are, who you are with, and what resources are close to you. A context aware system in this concept is one that "adapts according to the location of use, collection of nearby people and objects, as well as changes to those objects over time". Dey [28] defined context as "any information that can be used to characterize the situation of an entity", and a context-aware system is one that "uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task".

Other works [29–34] have reported the importance of context awareness in a Smart House environment.

3.2. History

The history of Smart Houses has been reported in other reviews [1,10]. One of the most relevant projects is the Smart House in Boulder, Colorado, which uses the adaptive control of home environment (ACHE) system and Neural Networks [35]. ACHE Smart House controls several functions of the house including temperature, lighting and heating, without the user having to configure them. The goal of ACHE is for the home to program itself based on neural network model by observing the person's "lifestyle and desires", and then learning to predict and adapt to their needs [35].

The MavHome project (Managing an Intelligent Versatile Home), from the University of Texas, is a home that behaves as a "rational agent" [36]. The MavHome aims to increase the comfort of its users while reducing the operation costs. The rational agent attempts to guess the mobility patterns and device usages of the inhabitants. The MavHome system is based on the LeZi-update algorithm for tracking users [37]. The LeZi-update algorithm is explained in Section 3.4.3.

In Florida, the "GatorTech Smart House" project was developed [38]. The GatorTech is composed of several single smart devices such as bed, mailbox, floor, entrance door, and others. These individual smart devices include sensors and actuators that are connected to an "operational platform designed to optimize the comfort and safety of an older person" [1,38].

In the United Kingdom, Orpwood et al. [39] described a Smart House adapted for people with dementia. In their report, most devices in the Smart House were constantly supervised through several sensors installed in the house. Their report also suggested that Smart Houses should have minimum interaction with the user in order to make it suitable for people with dementia.

CarerNet, also developed in the United Kingdom, can be summarized as a Smart House "to improve and enhance the quality of life of the elderly and the disadvantaged by the utilization of technology in support of their ability to function independently within their local environment" [40]. CarerNet collects physiological data, determines the patient's lifestyle and environmental awareness through the use of several devices such as thermometer, Infra-red (IR) badges, Electrocardiography (ECG), galvanic skin response, among others.

In Finland, a personal wellness monitoring system named TERVA enables the supervision of "wellness-related variables at home" from a short to a long period of time [41]. The TERVA operates on a computer and communicates with several different measurement instruments. The variables measured range from blood pressure, user's temperature, weight, beat-to-beat heart rate intervals, respiration, movements, etc. In addition, a behavioural diary is kept to monitor daily wellbeing.

Another Smart House was developed in Finland using capacitive indoor positioning and contact sensing [42]. The goal was to recognize the activities of the person living in a 69 m^2 Smart House. Their system used electrodes embedded in the floor in order to detect a person at floor level, and then determine the person's interaction with household items (table, bed, refrigerator and sofa).

In Ireland, the Great Northern Heaven Smart Home was developed [43]. Sixteen Smart Homes were built to detect behavioural patterns in the ADL for older people. A combination of ambient sensor monitoring together with self-reported data and behaviour recognition was implemented. Their system used machine learning techniques and pattern recognition to test and predict the well-being of the residents.

The Aurama awareness system developed in the Netherlands supports ageing in place and uses several devices such as photo frame to detect changes in behaviour patterns [44]. Other technologies used are the RF signal to detect the presence of the residents, and bed sensors to detect the number of times the older person gets out of bed. Three generations of the Aurama were reported, and each generation was improved according to field work testing.

The SPHERE project deals with sensing, networking, and machine learning for residential healthcare [45]. Their idea is to fuse sensor data and create a rich dataset to detect and manage various health conditions. SPHERE uses physiological (wearable) signal monitoring, home environment monitoring, and vision-based monitoring. Their approach to the multimodality sensing system is fully integrated with "intelligent data processing algorithms driving the data collection" [45].

In the Netherlands, the Unattended Autonomous Surveillance (UAS) system was developed to support ageing in place [46]. The systems uses ZigBee network and wireless sensors placed around the house. The system also uses cameras that are activated in case of emergency.This system is tested by older adults in the towns of Baarn and Soest in The Netherlands.

Another project in the Netherlands installed a house for testing [47]. A total of 14 state-state change sensors were installed in the house. The duration of the testing was 28 days and resulted in an annotated dataset available for the public.

3.3. Sensor Technology Devices

A number of sensor devices are used to supervise the activity of the inhabitant in the house. The information gathered from the devices is processed and stored for analysis and usage during the current and future state.

Several Smart Houses follow the concept of ubiquitous sensing, where "network of sensors integrated with a network of processing devices yield a rich multi-modal stream of data" [48]. Other Smart Houses also use Health and Usage Monitoring Systems (HUMS). HUMS refers to "sensors that monitor use and condition of a utility, and sub-systems that contain sensors, processors and algorithms" [49].

Sensors are placed throughout the Smart House to monitor the occupant's safety and supply different services [50]. Some examples are sensors for measurement of temperature, movement, distance, humidity, acoustic, water flow, gas, door and window states.

Environmental sensors are used to detect the interaction between the user and objects to help to recognize human daily activity. [51]. These include sensors embedded in bed, chairs, kitchen appliances, etc.

Motion sensors detect movement and comprise optical, microwave, infra-red, acoustic sensors, etc. Motion sensors can be viewed as an application that can provide tranquillity to the occupant, plus they are usually unobtrusive. A network of wireless motion sensors is also used where some of them are combined with contact sensors on doors [52,53].

Motion wireless infra-red proximity sensors are used the In-Home Monitoring System (IMS) [53,54]. These motion sensors can be used in Smart Houses for security and fall detection for older adults [55], user tracking, and analysis of behavioural pattern [56].

At the Oregon Health and Science University, infra-red motion sensors were used to record occupants' movements [57]. These infra-red sensors were placed in every room in the Smart House. Magnetic contact sensors were also placed on doors to "track the flow of visitors" or to track whether anyone was in the house. However, a drawback of this was that the inhabitant had to wear radio-frequency identification (RFID) tags to connect with the receiver in order to be identified. This drawback was exacerbated if there was more than one occupant in the house at any given time, since each person had to be tagged with RFID

Tracking floors can detect where the person is [5,38]. Multiple objects can be recognized simultaneously by analysing the object's weight [58].

Ultrasonic sensors are also used to detect motion. The Gator Smart House implements ultrasonic sensors to detect occupant movement, orientation, and location awareness for older adults in Smart Houses [3,38]. Multiple receivers enable varying distances to be calculated from each receiver, thereby identifying an accurate location[3].

Cameras and movement detection sensors may work together in several scenarios. William et al. [50] reported a distributed smart camera network whose function was to localize and detect users falls. The system used low-power cameras with mote-class sensors (sensor nodes), creating a wireless network infrastructure [50]. In addition, the cameras used a decentralized procedure for detecting falls.

Another example of the use of cameras are the ones that are sporadically taking images of the environment. The images taken are used to detect "contextual information"; for instance, if the person is sleeping, this is inferred by the lack of movement [59]. Small low resolution cameras (i.e., 352×288 pixels) are preferred in Smart Houses because they are easier to deploy, require less bandwidth network connection and less power, and are easier to wire to a power source to do the processing. In contrast, large cameras can lead to occlusion [50].

Sensors for detecting fever have been developed to measure the fever based on thermal imagery analysis [60]. The fever detectors use thermal camera that can be placed anywhere in the Smart House (above a bed, bathroom area).

Another project used sensors placed in a room to localize the person using Impulse–Radio Ultra–WideBand (IR–UWB) [61]. A base station was used to receive the sensor data and coordinates of a tag. Using IR-UWB enabled estimates to be made of the distance to the tag using Round-Trip-Time (RTT) algorithms.

Wireless sensor nodes (SNs) are also used in Smart Houses. SNs are small devices with computing (processing units), wireless communication (radios) and sensing (sensors) capabilities [62]. A logical correlation-based sleep scheduling mechanism (LCSSM) was implemented to reduce the energy consumption of wireless SNs [62]. Another study implemented a low-power, low-frequency bandpass integrated CMOS filter for passive infra-red (PIR) sensors in wireless SNs, also reducing the power consumption [63].

PIRs were also used together with flexifore sensors in a Smart House project to detect the occupancy of the person in objects (sofa, toilet, bed, chairs, etc) [64]. Flexiforce sensors were implemented with a real-time dynamic threshold to enable a more accurate reading of the sensor output.

The Aware Home Research Initiative developed a gesture pendant with a camera [5,65]. This wireless device allows the person to use hand movements to give commands to the Smart House. The commands range from door opening, light dimming and raising the thermostat temperature. The gesture pendant was designed for people with impaired motor skills, vision or mobility [65].

Wang et al. [66] also developed a "multi-modal wearable sensor platform" in order to identify the interactions between multiple users in a Smart House environment. The platform integrated an audio recorder, accelerometer, temperature, humidity and light measurement, and RFID wristband reader.

Another device is a wrist sensor worn by older adults, where Multi Perceptron (MLP) Neural Networks (NN), Radial Basis Function (RBF) and SVM were implemented for the training of the classification modelling [67].

A project using wearable technology together with mobile devices is the city4Age project [68]. Other projects also implemented smart phones to recognize human activity by using the integrated accelerometer, gyroscope, GPS and camera [51].

Accelerometers in wrist watches have been used for monitoring [69]. The main idea is to recognize the basic movements of the person (lying, sitting, standing, walking, running, going up or down the stairs, and working at a computer). The signal collected is sent to a personal server through RF. Another accelerometer named Opal is used to record hand movements to detect cleaning tasks [70]. Opal used a hierarchical window approach based on the dynamic time warping algorithm.

Korel and Koo [71] reported context-aware sensing using Body Sensor Networks (BSN) for continuous patient monitoring, in order to detect life threatening abnormalities. The patient wears or has an implanted device to monitor any physiological state (e.g., blood pressure, heart rate). Their research focused on context-aware sensing and compared Bayesian Networks, Artificial Neural Networks and Hidden Markov Models. The report concluded that none of the analysis methods is better than the other, since each method addresses different issues.

Within wearable devices, innovations with the micro thermoelectric generator (uTEG) were reported to improve monitoring biometric devices [72]. uTEG is energy autonomous and maintenance free, and is adapted for wear on human skin.

Other wearable devices for Smart Houses have been reported [73–75]. However, this section is a summary of some of the sensor devices used within a Smart House.

3.4. Analysis Methods

Several methods have been implemented to optimize the learning process of users activities and behaviour in Smart Houses. For an unobtrusive Smart House, the system should be able to learn the user's ADLs and behaviours without actively involving the user in the learning and training process [23].

Ideally, the system should entail a continuous learning process since the user's activities and behaviour change over time [23]. In this section, some of the most common methods for activity recognition and behaviour analysis/modelling are described, and Figure 3 shows a schematic representation of these analysis methods.

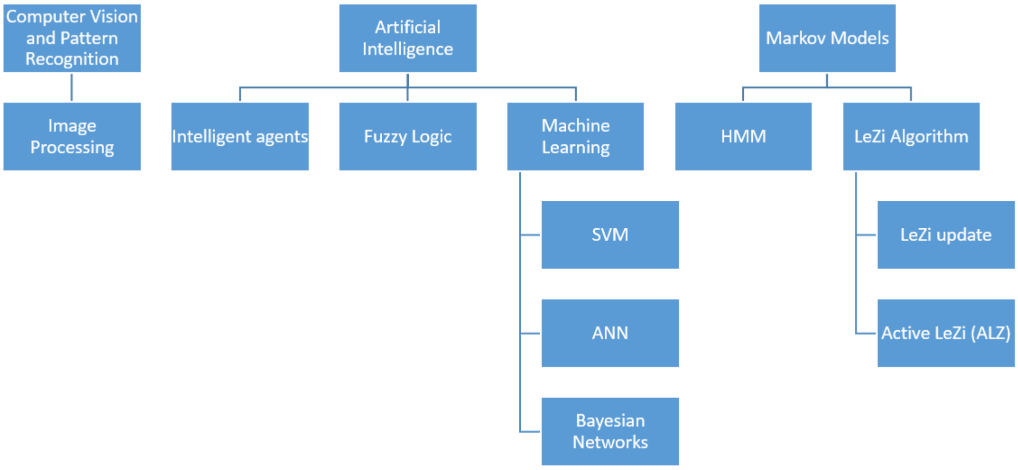

Figure 3. Analysis Methods.

3.4.1. Computer Vision and Pattern Recognition

Computer vision "describes the world that we see in one or more images and reconstructs its properties, such as shape, illumination, and colour distribution" [76]. The use of computer vision in Smart Houses comes together with the concept of pervasive computing. Pervasive computing is defined as "computing everywhere", "things that can think" or the integration of computers into the everyday physical world [77].

An important aspect of pervasive computing is the construction of predictive models of human activities and behaviours from sensor data. These predictive models allow the surroundings to be "aware of activities" carried out in it [77]. This concept can be applied to support older adults in a Smart House. Some of the work with computer vision and pattern recognition include face detection and recognition, optical character recognition, medical imaging, motion capture, fingerprint recognition and biometrics, body-part tracking, gesture understanding, morphing, and whole-body tracking, among others [76,78].

Mihailidis et al. [77] stated that computer vision can be used to build rich predictive models of human behaviours. Sensors installed at the Smart House enable the environment to be conscious of the user activities. For example, biometric identification uses pattern recognition techniques in order to identify people by their physiological characteristics. Also, face or voice recognition systems can be installed in the Smart House. A variety of commercial face recognition software is available and capable of high-accuracy recognition [79]. These recognition methods are unobtrusive and passive for the user.

Leo et al. [80] conducted a full research on the use of computer vision for assistive technologies, where a section was dedicated to human activity recognition. They reported how computer vision is used for tracking the person's silhouette or specific parts of the body, and later machine learning techniques were applied to recognize the activity of the person.

The gesture pendant device, described in Section 3.3, implemented computer vision techniques where a video is analysed and gestures are recognized [65]. Mihailidis et al. [77] focused on using computer vision within pervasive health care, and developed a sensing agent as part of an intelligent environment to support and orient older people.

At the Helsinki University of Technology [79], a neural net was used for face recognition tasks within a smart environment.

In Norway, Bu [81] also developed a computer vision-based system at Telemark University College (TUC). The system detected and localized people in a given room, recorded the past activity of people in a database, and notified a third party if abnormal behaviour was found. Other research at TUC, by Jaramillo [82], was on real-time activity tracking. The system used a camera where privacy was guaranteed by not storing images, and a rather volatile memory was used for process and analysis.

In addition, ongoing research at the University College of Southeast Norway (USN) focuses on identification of some of the components used to automatically track the activities of people living alone [83,84]. The research at USN consists of using mathematical models, computer science methods, a discrete event oriented framework, and tools to analyse data from sensors placed at the person's home, and using the information gathered to model the user's behaviours or routines.

Image Processing

Image processing refers to the use of images taken by cameras and later processed using mathematical algorithms. Some of the work of image processing includes grey-scale appearance modelling, shape analysis, colour classification, face pattern detection, background removal, plus more. In Smart Houses, image processing is able to track the location of the person and to identity the people in the house.

Krumm et al. [78] created a multi-camera system where the cameras track or sense the user. For example, when a person is watching a film, then leaves the couch, the film is paused until the user returns to the couch. Krumm's system utilized distributed computing, geometric modelling and sensing [78].

Darrell et al. [85] used person tracking for interactive entertainment and virtual environments. The system used "depth estimation to eliminate background effects, colour classification for fast tracking, and pattern detection to discriminate the face from other body parts" [85].

3.4.2. Artificial Intelligence (AI)

Artificial intelligence attempts to build intelligent entities. According to Russel and Norving [86], AI is concerned with thought processes, reasoning, behaviour and rationality. Thus, a computer or entity with artificial intelligence should be able to simulate human thoughts and actions, and rational thoughts and actions.

Intelligent Agents

Intelligent agents refer to software-based computer systems that have reactivity, social abilities, co-operativity, autonomy, rationality, pro-activity, and mobility properties, and are suitable for dealing with flexible monitoring in Smart Houses [87–89]. An agent is a software module or device that can conceptualize its environment through the use of sensors. Such agents can also act on the environment using effectors.

Another definition of an agent is any "independent hardware/software co-operation unit" capable of understanding the surroundings (through sensors) and answering to stimuli in accordance with predefined individual behaviours [87,90]. Agent functionalities include sensing, decision, action, computer network and database.

Several agents used together are called a multi-agent systems (MASs). MASs are capable of sharing information to one another and creating "collaborative group" behaviours to reach a single goal [90,91]. MASs can model complex systems; likewise, the agents can interact with each other directly or indirectly. An indirect interaction may be by acting on the environment, a direct interaction may be via communication and negotiation. Another property is that agents may choose to cooperate for mutual benefit or compete to satisfy their own goals [89].

Wang and Wang [87] used several intelligent agents that operate autonomously and cooperate with each other to perform their task. In Wang's system, intelligent agents were classified in five categories according to their functions, namely: user agent, monitoring scheming agent, searching agent, diagnostic agent, and information agent.

Reaz et al. [22,92] used MAS, modelling VHDL, and Field Programmable Gate Array (FPGA) for hardware prototyping in a Smart House environment. In addition, Reaz also used Active-Lezi as the prediction unit.

Alam et al. [17] developed a multi-agent system to track the user for task isolation. Their result showed successful identification of the inhabitant activities of various lengths. A Smart House (CASAS) was designed based on user behaviour change. CASAS is able to adapt to a person's changes in discovered patterns, and "can automatically update its model to reflect the changes" [19].

Hannon and Burnell [93] studied the mechanisms for creating intelligence in natural and artificial systems. The system implemented task-based modelling, where capabilities or functionalities could be added incrementally. The ThinkHome [94] implemented a MAS system and knowledge-base (KB) system.

The MavHome [36,37] used cooperating agents distributed across the Smart House in accordance with location and appliances. The agents followed a hierarchical layered approach comprising of an information or data acquisition layer, information processing layer, a communication layer and a decision-making layer.

Fuzzy Logic (FL)

Fuzzy logic was developed by L.A. Zadeh in 1965 and is excellent for performing automated reasoning [95]. As stated by Zadeh, the concept used in fuzzy logic is partial membership: "A fuzzy set is a class of objects with a continuum of grades of membership" [96]. Fuzzy logic is used for application such as diagnosis, control system, pattern recognition, and image processing, where higher level reasoning and inference are needed [95,97]. Fuzzy logics are commonly used in many household devices, including washing machines, toasters, microwave ovens, etc. [97].

Fuzzy logic is used for imprecision and uncertainty issues, and works in a similar manner to human reasoning, where incomplete data or inaccurate data is presented [95]. Fuzzy logic executes inference mechanisms following the IF-THEN condition, which "define the dependences of fuzzified input and output of system" [98].

An example of the IF-THEN rule is given by Vainio et al. [23], where an adaptive fuzzy control system for Smart Houses was developed. In Vianio's scenario, a lighting system was used as a test, where "IF person IS present AND outdoor lighting level IS dark THEN lighting power IS full".

Zhang et al. [98] presented a Smart House environment combining Fuzzy logics with a fuzzy neural network (FNN). The system controlled an alarm clock to create an appropriate "lead time". Data such as weather and traffic conditions were acquired from the Internet, and then FNN and FL were used to compute an appropriate alarm time depending on the external data available.

Medjahed et al. [99] used fuzzy logic in a pervasive multi-sensor environment for a Smart House health-care monitoring system. The system consisted of a multimodal platform with several sensors installed throughout the house to collect data. The data was later processed and analysed using fuzzy logic, which allows flexibility when combining modalities or adding more sensors.

The advantage of using fuzzy logic is that it is good for approximate reasoning, however it lacks learning abilities and adaptive capacity [97].

Machine Learning

Machine learning relates to the idea that computers can have the "ability to learn without being explicitly programmed" [100]. The great advantage of machine learning is that it eliminates the need for detailed programming efforts by letting the computer learn from experience.

Artificial Neural Networks (ANN): An interconnected group of nodes that uses learning algorithms to simulate the function of the brain. Hebb [101] started the work on Neural Networks (NN) and it was further developed by Hopfield [102], Rumelhart [103], and Widrow [97,104].

ANN is a promising tool that offers many attributes, including adaptability, massive parallelism, robustness (depending on the training), and inherent capability to handle non-linear systems [97,105]. ANN gives the advantage of performance improvement through learning using parallel and distributed processing [105]. In addition, ANN can model systems without a need for a-priori knowledge [106], and NN are low-level computational algorithms that have proven to perform well in processing numerical data [97].

Several researches showed the potential of neural networks in solving difficult optimization problems [105]. ANN is widely used for image processing, function mapping, classification, and pattern recognition [105]. In Smart Houses, ANNs are usually used for learning the habit of the user, depending on a varying number of parameters [106].

Growing Self-Organizing Maps (GSOM) are a type of self-adaptive neural network used by Zheng for the detection and recognition of ADLs [20]. The system employs a data mining environment technique, improved pattern discovery techniques, as well as visualization and interpretation. In addition, multi-resolution and hierarchical clustering analysis were also used.

Bayesian networks: A Bayesian network is a probabilistic graphical model for representing a set of random variables and their conditional dependences. Each node in the network represents variables, where "each node is conditionally independent from its nondescendent given its parents" [107].

Bayesian networks are commonly used in pervasive computing to reason about uncertainty, where context awareness is often required for autonomy and flexibility [108]. The term context, as described in Section 3.1.2, refers to any kind of information that can potentially be "used to characterize the situation of a person, physical or computational object, or place" [108,109].

At the National Taiwan University, Bayesian networks were used together with assistance from reliability factors and location information [110]. The overall robustness and performance for location-aware activity to establish ambient intelligence applications was improved.

Petzold et al. [111] used Bayesian networks to investigate machine learning techniques in order to dynamically predict room sequence, duration of stay, and the time when the person entered a room. The in-door system worked by comparing several methods of prediction. The research concluded that Bayesian networks' accuracy on "next location prediction" was no more than 90%, and the accuracy of "duration prediction" was about 87%. Petzol's investigation also added that the prediction between Bayesian network and neural network had the same range of accuracy.

Harris and Cahill [112] implemented a context-aware power management (CAPM) framework. CAPM effective power management relied on Bayesian networks that collected data from multi-modal sensors and then predicted the person's behavioural patterns. Park and Kautz [113] built a dynamic Bayesian network (DBN) computer-based recognition for ADL through the combination of "multi-view computer vision and radio-frequency identification (RFID)-based direct sensors".

Fox et al. [114] used Bayesian filter techniques for location awareness. Their research included Kalman filters, grid-based approaches, topological approaches, multihypothesis tracking, and particle filters. Rahal et al. [115] used Bayesian particle filtering based on Fox research to localize the occupant through several anonymous sensors placed throughout a Smart House.

Support Vector Machine (SVM): Support vector machine (SVM) is a computer algorithm that learns through the use of examples to classify objects [116,117]. SVM is used in security for recognizing fraudulent credit card activity and in in digit handwritten recognition. Another use is in biomedical applications, e.g., "automatic classification of microarray gene expression profiles" [116].

SVM was created by Vapnik [118] and further developed by Boser et al. [117]. The algorithm automatically tunes the classification function capabilities through maximizing the margin between the training patterns and the decision boundaries. The margin is any positive distance from the decision hyperplane. SVM is trained by choosing the current worst-classified pattern, which is the one on the incorrect side of the current decision boundary, farthest from that boundary [119]. The result of the classification function is solely dependent on supporting patterns.

SVM has been used for Speech Emotion Recognition (SER) in the field of e-learning [120]. The emotional state of a human being is identified by analysing the generation mechanism of the speech signal of a person's voice. Some features containing emotional information are extracted from the voice, and pattern recognition methods are applied to identify emotional states.

Fleury et al. [121] used SVM in a Smart House to monitor (through sensors) the older adult at home, with a view to early detection of the loss of autonomy. The data collected by the sensors is later analysed using SVM to classify seven activities of daily life, i.e., hygiene, eating, sleeping, and so on. Fleury's experiment was tested with 13 young subjects in order to find the different activity models, and subsequently test the SVM classification algorithm using real data.

3.4.3. Markov Model

A Markov model is a stochastic model generally used to model randomly changing systems. A Markov model works assuming that future states are solely dependent on the present state and not on the previous sequence of events. Markov models are particularly useful for decision problems that involve continuous risk over time, or where timing of an event is important or where events happen repeatedly.

Markov models are used in Smart Houses for several purposes. Brdiczka et al. [26] implemented the concept of context awareness to model human behaviour. Cameras and audio sensors were used to collect data and then Markov models were used to learn the user's behaviour.

Hoey et al. [6] developed a handwashing assistance system using the Markov model. The system consisted of cameras for tracking and decision-making processes using a partially observable Markov decision process (POMDP).

Hidden Markov Models (HMMs)

HMMs are a "subclass of Bayesian networks known as dynamic Bayesian networks" [107]. HMMs are ubiquitous and are used for modelling time series data.

HMMs represent probability distributions over observation sequences. HMMs are commonly used in speech recognition systems, computational molecular biology, data compression, pattern recognition, computer vision, and artificial intelligence [107]. The use of HMMs in computer vision includes object tracking and image sequence modelling.

Other extensions of HMMs have been used in Smart Houses for activity recognition and interleaved activity recognition [122,123]. These extensions include Hidden semi-Markov model (HSMM), Abstract HMM, Hierarchical HMM, and Switching Hidden Semi-Markov model (S-HSMM).

Duong et al. [122] implemented S-HSMM for activity recognition and abnormality detection in a pervasive environment. S-HSSM is a two-layered extension of the hidden semi-Markov model (HSMM). The results from Doung's investigation showed that S-HSMM perform better for classification and abnormality detection tasks than HSSM because there is no need for pre-segmented training data.

LeZi Algorithm

Lezi refers to Lempel–Ziv data compression algorithm [124]. The LeZi algorithm is a prediction algorithm and uses Markov encoders of growing order models to predict the next symbol [125,126]. Incremental parsing algorithm introduces another technique for gradually changing the Markov order over time at a suitable rate. For Smart Houses, it is very useful to predict the next event that will occur, e.g., to predict the inhabitant activity can help to automate interactions with the environment and to improve the inhabitant's comfort [125].

LeZi-update: LeZi-update captures sampled messages and processes them in chunks, delaying the actual update for some sampled symbols [36]. The LeZi-update algorithm observes and follows all potential contexts inside a given phrase. For tracking, Lezi-update learns the user's movement history, then it "builds a universal model by minimizing the entropy, and predicts future locations" accurately [127].

The Lezi-update algorithm is able to predict the user's present location successfully, and it can also be extended to other context predictions such as activity, trajectories, anomaly detection, and resource provisioning [127,128].

Active LaZi (ALZ): ALZ is an enhancement of the Lezi-update. ALZ applies the principle of information theory in order to subsequently process sequences of historical actions. The MavHome project uses ALZ to "predict, reason about, and adapt" the home for its users [37,125].

3.4.4. Methods Summary

Table 1 shows a summary of the most common analysis methods that have been implemented in Smart House Technology. This table is not exhaustive, but it provides a foundation for the most common analysis algorithms in the development of Smart Houses from 2000 to 2016 according to the search methodology used in this review.

Table 1. Most Implemented Methods in Smart Houses.

Method	Author	Title
Bayesian network	Park and Kautz [113]	Hierarchical Recognition of Activities of Daily Living using Multi-Scale, Multi-Perspective Vision and RFID
	Rahal et al. [115]	Bayesian Filtering and Anonymous Sensors for Localization in a Smart Home
	Fox et al. [114]	Bayesian Filtering for Location Estimation
	Harris and Cahill [112]	Exploiting User Behaviour for Context-Aware Power Management
	Petzold et al. [111]	Prediction of Indoor Movements Using Bayesian Networks
	Lu and Fu [110]	Robust Location-Aware Activity Recognition Using Wireless Sensor Network in an Attentive Home
	Gu et al. [108]	A Bayesian Approach for Dealing with Uncertain Contexts
	Hoey [129]	Tracking using Flocks of Features, with Application to Assisted Handwashing
	Tapia et al. [130]	Activity Recognition in the Home Using Simple and Ubiquitous Sensors
	Dimitrov et al. [131]	Structured Learning of Component Dependencies in AmI Systems
	Lu et al. [132]	Hybrid User-Assisted Incremental Model Adaptation for Activity Recognition in a Dynamic Smart-Home Environment
Naives Bayes/Decision Trees	Maurer et al. [133]	Activity Recognition and Monitoring Using Multiple Sensors on Different Body
	Papamatthaiakis et al. [134]	Monitoring and Modeling Simple Everyday Activities of the Elderly at Home
Decision Trees	Bao and Intille [135]	Activity Recognition from User-Annotated Acceleration Data
	Vainio et al. [23]	Proactive Fuzzy Control and Adaptation Methods for Smart Homes
	Bieber et al. [136]	Using Physical Activity for User Behavior Analysis
	McBurney et al. [137]	Adapting Pervasive Environments through Machine Learning and Dynamic Personalization
	Fan et al. [138]	Private Smart Space: Cost-Effective ADLs (Activities of Daily Livings) Recognition Based on Superset Transformation

Table 1. *Cont.*

Method	Author	Title
Computer vision	Brumitt et al. [139]	EasyLiving: Technologies for Intelligent Environments
	Darrell et al. [85]	Integrated Person Tracking Using Stereo, Color, and Pattern Detection
	Krumm et al. [78]	Multi-Camera Multi-Person Tracking for EasyLiving
	Bu [81]	Development of a Non-Invasive Computer Vision System for Monitoring Elderly People Activity at Home
	Jaramillo [82]	Non-Invasive Human Activity Tracking System
	Nordal [140]	Computer Vision System
CV/Int. Agents	Mihailidis et al. [77]	The Use of Computer Vision in an Intelligent Environment to Support Aging-in-Place, Safety, and Independence in the Home
Correlated Pattern	Sim et al. [141]	Activity Recognition Using Correlated Pattern Mining for People with Dementia
Gaussian Dist./PAM	Rashidi and Cook [19]	Keeping the Resident in the Loop: Adapting the Smart Home to the User
Kernel Density Estimation	Hayes et al. [52]	An Unobtrusive In-home Monitoring System for Detection of Key Motor Changes Preceding Cognitive Decline
Mix Models	Barger et al. [56]	Health-Status Monitoring Through Analysis of Behavioral Patterns
Maximum Likehood	Zhang et al. [142]	Decision Support for Alzheimer's Patients in Smart Homes
T-Pattern	Kropf et al. [143]	A Modular and Flexible System for Activity Recognition and Smart Home Control Based on Nonobtrusive Sensors
Hierarchical Classifiers Alg(HCA)	Peng et al. [144]	A Novel Data Mining Method on Falling Detection and Daily Activities Recognition
Quadratic Discrimi. Classifier	Soviany and Puscoci [145]	A Hierarchical Decision System for Human Behavioral Recognition
PCA/K-nearest Neighbors	Fahad et al. [146]	Activity Recognition in Smart Homes Using Clustering Based Classification

Table 1. *Cont.*

Method	Author	Title
Fuzzy Logic	Medjahed et al. [95]	Human Activities of Daily Living Recognition Using Fuzzy Logic For Elderly Home Monitoring
	Seki [147]	Fuzzy inference based non-daily behavior pattern detection for elderly people monitoring system
	Zhang et al. [98]	Information Fusion Based Smart Home Control System and Its Application
	Medjahed et al. [99]	A Pervasive Multi-sensor Data Fusion for Smart Home Healthcare Monitoring
	Ros et al. [148]	A System to Supervise Behaviours Using Temporal and Sensor Information
	Mowafey et al. [149]	Development of an Ambient Intelligent Enviroment to Facilitate the Modelling of Well-Being
	Shell and Coupland [150]	Improved Decision Making Using Fuzzy Temporal Relationships within Intelligent Assisted Living Environments
	Ros et al. [151]	A Fuzzy Logic Approach for Learning Daily Human Activities in an Ambient Intelligent Environment
	Chan et al. [152]	Towards Intelligent Self-care: Multi-sensor Monitoring and Neuro-fuzzy Behavior Modelling
Fuzzy Logic/Intelligent Agents	Hagras [153]	Creating an Ambient-Intelligence Environment Using Embedded Agents
	Doctor et al. [154]	A Fuzzy Embedded Agent-Based Approach for Realizing Ambient Intelligence in Intelligent Inhabited Environments
	Mowafey and Gardner [155]	A Novel Adaptive Approach for Home Care Ambient Intelligent Environments with an Emotion-aware System
	Mowafey and Gardner [156]	Towards Ambient intelligence in Assisted Living: The Creation of an Intelligent Home Care

Table 1. *Cont.*

Method	Author	Title
Intelligent Agents	Alam et al. [17]	Human Activity Classification for Smart Home: A Multiagent Approach
	Sun et al. [90]	A Multi-Agent-Based Intelligent Sensor and Actuator Network Design for Smart House and Home Automation
	Ramos et al. [157]	Ambient Intelligence- the Next Step for Artificial Intelligence
	Wu et al. [158]	Service-Oriented Smart-Home Architecture Based on OSGi and Mobile-Agent Technology
	Gu et al. [159]	An Ontology-Based Context Model in Intelligent Environments
	Chen et al. [160]	An Intelligent Broker for Context-Aware Systems
	Cook et al. [161]	A Multi-Agent Approach to Controlling a Smart Environment
	Zhang et al. [162]	An OSGi and Agent Based Control System Architecture for Smart Home
	Czibula et al. [163]	IPA - An intelligent personal assistant agent for task performance support
	Reinisch et al. [94]	ThinkHome: A smart home as digital ecosystem support
	McNaull et al. [164]	Multi-agent Interactions for Ambient Assisted Living
	Ferrill et al. [165]	An agent architecture for adaptive supervision and control of smart environments
	Spanoudakis and Moraitis [166]	Engineering ambient intelligence systems using agent technology
	Frey [167]	AdAPT -A Dynamic Approach for Activity Prediction and Tracking for Ambient Intelligence
	Bosse et al. [168]	An Ambient Agent Model for Monitoring and Analysing Dynamics of Complex Human Behaviour
I.A./Bayesian Net	Kushwaha et al. [169]	An intelligent Agent for Ubiquitous Computing Environments: Smart Home UT-AGENT
Intelligent Agents/Lezi	Reaz et al. [92]	Prototyping of Smart House: A Multiagent Approach
	Cook et al. [37]	MavHome: An Agent-Based Smart Home
Lezi	Das et al. [36]	The Role of Prediction Algorithms in the MavHome Smart Home Architecture
	Gopalratnam and Cook [125]	Online Sequential Prediction via Incremental Parsing: The Active LeZi Algorithm
	Roy et al. [128]	Location Aware Resource Management in Smart Homes

Table 1. *Cont.*

Method	Author	Title
Markov Model/Intell. Agents	Zhang and Gruver [170]	Distributed Agent System for Behavior Pattern Recognition
Markov Model	Brdiczka et al. [26]	Detecting Human Behavior Models From Multimodal Observation in a Smart Home
	Duong et al. [122]	Activity Recognition and Abnormality Detection with the Switching Hidden Semi-Markov Model
	Kautz et al. [171]	Foundations of Assisted Cognition Systems
	Kim et al. [123]	Human Activity Recognition and Pattern Discovery
	Helal et al. [172]	Smart Home-Based Health Platform for Behavioral Monitoring and Alteration of Diabetes Patients
	Hoey et al. [6]	Automated Handwashing Assistance for Persons with Dementia Using Video and a Partially Observable Markov Decision Process
	Want et al. [66]	Recognizing Multi-User Activities Using Wearable Sensors in a Smart Home
	Starner et al. [65]	The Gesture Pendant: A Self-illuminating, Wearable, Infra-red Computer Vision System for Home Automation Control and Medical Monitoring
	Boger et al. [173]	A Planning System Based on Markov Decision Processes to Guide People with Dementia Through Activities of Daily Living
	Bruckner et al. [174]	Behavior Learning Via State Chains from Motion Detector Sensors
	Rashidi and Cook [175]	COM: A Method for Mining and Monitoring Human Activity Patterns in Home-Based Health Monitoring Systems
	Van Kasteren et al. [47]	Accurate Activity Recognition in a Home Setting
Markov Model/NNs	Mihailidis et al. [176]	The COACH Prompting System to Assist Older Adults with Dementia Through Handwashing: An Efficacy Study

Table 1. *Cont.*

Method	Author	Title
Neural Network	Zheng et al. [20]	Human Activity Detection in Smart Home Environment with Self Adaptive Neural Networks
	Rivera et al. [177]	Automated Discovery of Human Activities Inside Pervasive Living Spaces
	Hannon and Burnell [93]	A Distributed Multi-Agent Framework for Intelligent Environments
	Kussul and Skakun [178]	Neural Network Approach for User Activity Monitoring in Computer Networks
	Bourobou et al. [18]	User Activity Recognition in Smart Homes Using Pattern Clustering Applied to Temporal ANN Algorithm
	Zhang et al. [98]	Information Fusion Based Smart Home Control System and its Application
	Rivera et al. [179]	A Neural Network Agent Based Approach to Activity Detection in AmI Environments
	Acampora et al. [180]	Interoperable Services Based on Activity Monitoring in Ambient Assisted Living Environments
Neural Network/SVM	Chernbumroong et al. [67]	Elderly Activities Recognition and Classification for Applications in Assisted Living
SVM	Fleury et al. [121]	SVM-Based Multi-Modal Classification of Activities of Daily Living in Health Smart Homes: Sensors, Algorithms and First Experimental Results
	Pan et al. [120]	Speech Emotion Recognition Using Support Vector Machine
	Williams et al. [50]	Aging in Place: Fall Detection and Localization in a Distributed Smart Camera Network
	Yazar et al. [181]	Fall Detection Using Single-Tree Complex Wavelet Transform
	Fahad et al. [182]	Activity Recognition in Smart Homes with Self Verification of Assignments
SV Data Description	Shin et al. [183]	Detection of Abnormal Living Patterns for Elderly Living Alone Using Support Vector Data Description

3.5. Challenges

Smart Houses have shown to be feasible and cost-effective projects to help older adults to remain at home for as long as possible, reduce bills, or just improving comfort for the user. Nevertheless, Smart Houses present some challenges that need to be overcome.

3.5.1. Technological Challenges

In general, depending on the technology used, most Smart Houses tend to have high prices, which represents a barrier to access for low-income owners. Also, when deploying the Smart House, the installation process of the different sensors or devices may be arduous. For example, the Gator Tech Smart House reported some challenges when installing the smart floor in their project [38]. Another issue is the scalability of the project. Many Smart Houses are in a prototype phase with promising results, but no one can actually live there, such as the Matilda Smart House [38].

Another technological challenge is the learning algorithm used by the Smart House system. There are limitations in all the analysis methods mentioned in Section 3.4, in addition to a high complexity cost [6] and reliability of the sensory system [1]. Moreover, for most of the analysis methods, the adaptability of the system depends on the behaviour of the user. If the intended target is people with progressive diseases such as Alzheimer's, the system will not be able to keep learning from the user's habits.

Regarding the analysis methods, a disadvantage of using intelligent agents is standardization. There is still no standard agent communication, thus only agents using the same language can communicate with each other. This means that the user cannot have new types of devices that do not communicate with the ones already installed at his/her home.

Moreover, there is not an established Smart House open architecture that would allow manufacturers to build new devices for Smart Homes. This is inconvenient for most manufacturers and prospective users who wish to expand their Smart Home and connect different or new devices together. Therefore, Xu et al. [184] and Mihaylov et al. [185] have proposed standardized platforms.

Another important disadvantage of intelligent agents in that "the patterns and the outcomes of the interactions are inherently unpredictable" [186]. This means that since agents are autonomous, the behaviour and effects resulting from their interactions are uncertain. De-coupling is another drawback resulting from the autonomy of the agent.

Data integration is another issue that has not yet been solved. The large amount of data collected by the Smart House devices is not always handled properly by the AI modules. AI modules are not yet capable of dealing with large datasets. Also, the sharing of the data is not standardized or integrated. The Smart House, being part of the Internet of Things (IoT), is able to send data in different formats, and through different interfaces. Thus, data integration needs to be considered in Smart Houses in order to send the collected data to a determined storage system and then process it in an integrated manner.

The training period for the system can also be considered a technological challenge. As the Smart House adapts to the person living in it, there must be a period for the system to learn the behaviour of the inhabitant. From a commercial point of view, this learning period can be undesirable.

Another challenge reported in the MavHome project is that system coverage area is divided into zones; however, the paging process used by the MavHome becomes inefficient if there is an extensive number of zones covering the Smart House [36]. Finally, wearable devices in a Smart House represent challenges for their wearers [77]. If the person forgets to wear the device, the Smart House system may not work as intended.

3.5.2. Ethical Challenges

It is essential to study the ethical impact that the project will have on the users. If cameras are used, the privacy of the user must be respected. Some people may feel that the use of cameras is acceptable if the cameras do not identify the person, such as silhouette used by Leo et al. [80,187].

In addition, other matters such as security of the system, data leakage, possible replacement of human interaction by technology, and training or learning process for older adults are some of the ethical challenges to consider when implementing Smart Houses.

A study directed by Demiris et al. [16] reported the perceptions and concerns of 15 older adults towards Smart Houses. The participants had lived in the Aging in Place project which consisted of 32 smart apartments. The participants were over the age of 65. The results of the study suggested that older adults would benefit from the Smart Houses in terms of "emergency help, hearing and visual impairment assistance, prevention and detection of falls, automatic lighting, temperature, stove and oven safety control, intruder alarm, reminder systems, timely and accurate information on adverse drug events and contraindications".

Another study conducted at Georgia Tech's Aware Home [5] reported the assessment of 44 older adults aged 65 to 75. In general, some of them expressed concerns about too much assistive technology inducing the "loss of autonomy or decline in capability" [5].

Ideally, the Smart House should bring peace of mind to the older adult and their family. Smart Houses are supposed to provide a better and safer environment, reduce risks, avoid harm such as falling or fire, reduce utility costs if possible and provide other benefits [188]. In this regard, technology should only be used where the person using it or the caregivers understand in full the technology and thus are able to provide informed consent [55,84].

Also, in order for Smart House systems to function, user data is stored in databases. Thus, it is critical to verify that the user's information through the line of communication is safe and secure. The information about the older adult's activity in their home is sensitive, and confidentiality must be ensured, with no third party being able to intercept the user's data [1,189].

3.5.3. Legal Challenges

There are many legal challenges that arise when developing a Smart House system. The legal aspects vary according to the country in which the Smart House is being implemented. In Norway, a review [190] identified the following main legal challenges: data privacy, data access and management, stakeholders' interest, and informed consent of the users and/or the users' families.

In order for a person to accept monitoring in his/her own home, legal regulations need to be established to assess patient-identifiable data [191]. A number of legal and privacy issues need to be considered in relation to the processing and storing of data. The information that the Smart House system handles contains sensitive information about the user. Legal solutions therefore need to be secured in order to store data from the welfare technological equipment [190].

In addition, it must be established who will have permission to access, view and secure the data (audtiotape, video recording, and others) from the Smart House system, in order to prevent it from falling into the wrong hands [192]. Regarding the stakeholders interest, conflicts between the Smart House provider and the user may arise. Thus, it is important to clearly identify and seek consent from all the stakeholders. The stakeholders can be direct or indirect, and range from informal caregivers, relatives, or others [193].

4. Discussion

4.1. What Are Smart Houses?

Smart Houses have been under development for several decades, and promise to bring ease and peace of mind for the users. Smart Houses have been defined as any environment designed and built to help the user perform activities independently [1–3].

Smart Houses are designed for different types of users, from fully independent adults to older adults with disabilities and dementia. Thus, the function of a Smart House varies considerably depending on the target audience. Nevertheless, the overall purpose of a Smart House is to maximize the comfort and ease of living of the inhabitant as much as possible.

In order for the Smart House to help the user, the house needs to adapt to its user. This is generally done by learning the behaviour of the person. Therefore, the Smart House aims to learn from the person's activity and and actions, with a view to identifying repetitive patterns. This learning is done in order to model and predict the behaviour of the person, which is achieved by collecting data from sensors installed throughout the Smart House, and then applying different algorithms and/or data mining techniques.

In addition to learning from the user's activity and behaviour, the Smart House also needs to learn from the context, which is called context awareness. The concept is that the Smart House knows the surroundings and the environment, knows where the activity takes place, and knows who and where the user is [26,27]. This context awareness of the Smart House makes the prediction of the user's activity more accurate.

Among the most relevant Smart Houses projects developed are the ACHE home in Colorado, USA [35], the MavHome in Texas, USA [36], the GatorTech Smart House in Florida, USA [38], CareNet in the United Kingdom [40], the TERVA home in Finland [41], and others.

4.2. What Technology Devices Are Used in a Smart House Environment?

Several sensors are installed throughout the Smart House to obtain the data needed for the Smart House to function properly. The data gathered from the sensors is used to model and adapt the Smart House to the inhabitant, and also in several cases to reduce utility bills.

The sensors generally used are motion sensors, humidity sensors, acoustic sensors, temperature sensors, water flow sensors, positioning sensors, optical sensors, sensors on doors, pressure sensors, ultrasonic and infra-red sensors, among others. In principle, the more sensors a Smart House has, the greater the accuracy of data on activity and behaviour.

However, the large amount of sensors may increase the cost of installing a Smart House, making it undesirable for the user. In addition, many users may feel that installing too many sensors will be an intrusion, and will make their home an array of technological tools instead of giving the feeling of being at home [194].

Some Smart Houses also use wearable technology to increase the accuracy of the Smart House, for example, to know the user's location. However, not every user is willing to use an on-body wearable device. In addition, after a while, the person may forget to wear the device or remove the device if necessary at night [50].

4.3. What Analysis Methods Are Used in a Smart House Environment?

Different algorithms have been used for learning and predicting the user's activities and behaviour within the Smart House context. These algorithms vary according to the goals of the Smart House.

Section 3.4 refers to the most common analysis methods used: computer vision, pattern recognition, image processing, artificial intelligence, artificial neural networks (ANN), Bayesian networks, Markov models, fuzzy logics, LeZi algorithm, and Support Vector Machine (SVM). Other algorithms are also used to optimize the learning process of the Smart House, but the methods covered in this review are the most commonly applied and have the most promising results.

In order to obtain better results, the aforementioned analysis methods have been used either on their own or in combination. None of these methods can be said to provide 100% accuracy. Nevertheless, the learning and prediction functions are very promising.

Computer vision methods are used to detect the context of the Smart House by constructing predictive models of human activity and behaviour from the sensor data. However, there are some limitations on using computer vision in a Smart House system. One of them is the use of cameras, which some users may consider to be invasive. In addition, cameras may produce noisy images leading to data with uncertainties and limiting the accuracy of the results.

Image processing is sometimes used in combination with computer vision methods. Image processing techniques improve the image quality obtained from the cameras, then computer vision methods continue the recognition or learning task. However, a disadvantage is that processing large amounts of images can be computationally expensive.

Intelligent agents are modules that are able to sense the environment and create context awareness. Their task is to sense, act and make decisions, among other things. Their advantages are autonomy and asynchronism, whereby the user does not need to control or monitor the agent. However, the drawback is that autonomy can create uncertainty in the behaviour of the agent, and also de-coupling.

ANNs simulate the function of the brain through an interconnected group of nodes. ANNs have gained a lot of popularity lately because they enhance the learning and pattern recognition task. Also they have proven to be efficient because of their adaptability, robustness, parallelism, and other attributes [97,105]. Nevertheless, a drawback is that sometimes neural networks are not suitable for working in environments containing a dynamic sensor configuration. This is because each sensor in the ANN requires a singular input node, and also training is required for the configuration of each sensor set [99]. Another drawback is that ANN requires users to define in advance several learning parameter [20]. Thus ANN needs a lot of pre-defined training data from the user.

Bayesian networks represent conditional independences between a set of random variables and are a great advantage in Smart Houses because they can carry out uncertainty reasoning. Also, Bayesian networks have the attribute of interpolation. However, the disadvantages of Bayesian networks include computational difficulty and reliability. In order for the Bayesian network to compute the probability of a given branch in the network, all the branches need to be computed again, thus making it computationally expensive. In addition, Bayesian networks are useful only when the prior knowledge is reliable [195].

Markov models are used for randomly changing systems and problem decision-making. The great advantage of using Markov models in a Smart House is that the future only depends on the present state. However, when using HMM, the HMM requires training from a large set of data. Fuzzy logic is used to deal with uncertainty. Fuzzy logics use symbolic and numerical processing together, producing flexibility in the form of cognitive perspective [196]. However, Fuzzy logic also requires large training dataset to increase the accuracy of the algorithm.

The LeZi algorithm has been used to predict the user's location. The LeZi algorithm has major disadvantages such as the loss of patterns between two parsed substrings. Therefore, Active LeZi and the LeZi update algorithm were proposed. Active LeZi has also been combined with Markov models to predict the next state of the system. An advantage of the active LeZi is the high prediction accuracy obtained with a small training dataset [125].

The advantage of SVM is that training can be performed with small sets of data, whereas Bayesian classification or neural network methods cannot be used for small sets of data [121]. Nevertheless, SVM should not be used for large sets of data because finding the worst-case pattern is computationally expensive. For each update, the SVM algorithm must search again through the entire training set to find the worst-classified pattern [119]. Also, Burges mentioned that "Perhaps the biggest limitation of the support vector approach lies in choice of the kernel" and the "speed and size, both in training and testing" [197].

4.4. What Are the Current Challenges Involved in Deploying a Smart House?

As previously described in Section 3.5.2, the user's privacy must be respected and protected in every aspect. The communication lines of the system must be safe and secure, ensure confidentiality and that no unauthorized third party can have access to the user's personal data [1]. User data is regarded as sensitive data, and access by an unauthorized party can have detrimental consequences. Thus, it is essential to have proper legislation that deals with the issue of data privacy [190]. In addition, it is important to know who is responsible for what and when [191].

Likewise, diminishing of human interaction due to assisted technology is another downside of Smart Houses. If the user is an older adult, technology can turn physicians and nurses into medical technicians, hence reducing personal relationships for the person. Thus, technology threatens to replace any human contact that the older adult might have [1].

Also, the friendliness of the Smart House must be considered. User-friendly technology systems must be ensured. Not every user likes new technology; they may consider it difficult to use or be of the opinion that it requires extensive training. Hence, an ideal Smart House would require little or no user programming.

Moreover, acceptance of the system is critical to the development of Smart Houses. Satisfaction and acceptance of Smart Houses have been reported in several studies [1,198–200]. It is essential to ensure that the Smart House provides security and will not make the user feel vulnerable or guarded.

Another Smart House concern is the cost effectiveness. Technology used in some Smart House projects tend to have a high cost, thus making it prohibitively expensive for some prospective users. On the other hand, living at home rather than in a nursing home, is proven to be more cost effective [1,201].

Sensors introduce uncertainty that create errors in the information collected [45]. This could be due to malfunctioning in the sensors. In addition, signal to noise ratio can also corrupt the sensor's signal.

Informed consent is another issue when deploying Smart Houses. Demiris and Hensel [193] stated that "Informed consent is an individual's autonomous authorization of a clinical intervention or research participation" . The user needs to fully understand and be able to give informed consent to install a Smart House system at his/her own home. Therefore, the major components of informed consent are competence, disclosure, understanding and voluntary understanding [202].

In general, the legal and ethical aspects of Smart House systems are a considerable obstacles that may impede widespread adoption. Although some reports have studied the ethical, technological and legal challenges that Smart Houses present, there is still the need for more in-depth studies, research surveys and assessments on Smart Houses to optimize the use of this technology.

5. Limitations of the Study

A limitation of this study was the lack of conceptual information in the articles found. However, this limitation was overcome by searching specific articles where the theory was fully explained. Thus, in this review, 33 articles about the concepts or theory of the analysis methods were also included.

Another limitation was searching for the legal challenges. The legal aspects change depending on which country the Smart House is implemented. Therefore, a previous review conducted by USN on the legal challenges in Norway was the main source for the legal challenges section in this review.

Finally, the keyword search could be expanded to include more articles such as Smart Houses not only for older adults. Thus, the summary in Table 1 is not intended to be exhaustive.The main intention of the table is to provide a foundation for the most common analysis algorithms used in Smart House development for older adults over the last 16 years, according to the databases searched.

6. Future Research

Several algorithms have been used to detect and predict the user's behaviour and activity recognition. However, many of the algorithms mentioned in this review need further improvement. Moreover, the technology devices used lacked standardization and a legal basis to fully deploy a Smart House. Finally, there are still ethical and legal challenges that need to be addressed before the population can fully accept Smart Houses.

7. Conclusions

Smart Houses have proven to be a promising path for improving access to home care for the ageing population. The main purpose of Smart Houses is to ameliorate the lives of older adults. Moreover, Smart Houses also target the population in general, with a view to improving comfort and making their everyday lives easier

Various research has been conducted, as summarized in Table 1. Learning algorithm methods are a very important step in the design of Smart Houses. The Smart House should be able to learn the user's activities and behaviours to find patterns, and then use these patterns to "predict" the future behaviour of the user.

This review examines the most common analysis methods used in Smart House Welfare Technology over the last 16 years. The methods included in this review are: computer vision, pattern recognition, artificial intelligence, image processing, Bayesian networks, Markov models, fuzzy logic, the LeZi algorithm, and the support vector machine (SVM). A brief introduction is given of each method in the review, as well as examples from previous research of how these were implemented.

This review also includes the results on the history and the technological, ethical and legal challenges of Smart Houses, as well as the technology devices used.

Author Contributions: N.-O.S and C.F.P conceived and designed the study; V.G.S. performed the research, analyzed the data, and wrote the paper.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Database Search

For all the databases search, the following keywords were combined and used:

Keywords: smart house, smart home, welfare technology, assisted living, user's behaviour, review, ethical challenges, legal challenges, technological challenges, algorithm, analysis method, elderly or aged or older adult.

In this appendix, the search strategy for IEEEXplore and Scopus database are provided.

Appendix A.1. Search Strategy for IEEEXplorer Database

For all searches, the year range from 2000 to 2016 was defined.

- 1. First keyword combination: "user behaviour" AND (welfare technology OR smart environment OR assisted hous OR Smart House OR Smart Home OR assisted living) AND (elderly OR aged OR older adult) AND (algorithm OR analysis method)

  a. The option of Full Text Metadata was selected

  b. Total = 264 records found

- 2. Second keyword combination: "user behavior" AND (welfare technology OR smart environment OR assisted hous OR Smart House OR Smart Home OR assisted living) AND (elderly OR aged OR older adult) AND (algorithm OR analysis method)

  a. The option of Full Text Metadata selected was selected

  b. Total = 1172 records found

- 3. Third keyword combination: "pattern recognition" AND (welfare technology OR smart environment OR assisted hous OR Smart House OR Smart Home OR assisted living) AND (elderly OR aged OR older adult) AND (algorithm OR analysis method)

  a. The option of Metadata only was selected to narrow down the number of results

  b. Total = 51 records found

Appendix A.2. Search Strategy for SCOPUS Database

- 1. First keyword combination: ALL (((("user behaviour" OR "user behavior") AND (welfare technology OR smart environment OR assisted hous* OR smart house OR smart home* OR assisted living) AND (elderly OR aged OR older adult) AND (algorithm OR analysis method))))

a. Total = 6 records found

- 2. Seconds keyword combination: ALL ((("pattern recognition" AND (welfare technology OR smart environment OR assisted hous* OR smart house* OR smart home* OR assisted living) AND (elderly OR aged OR older adult) AND (algorithm OR analysis method))))

a. Total: 24 records found

Appendix A.3. Search Outcome and Selection Criteria

The databases of ACM Library, ScienceDirect, IEEE, Academic Search Premier (EBSCO), and SCOPUS were searched. The result of the combined records found is 4028.

Using Endnote, the following articles were removed:

- (1) Total records found = 4028
- (2) Duplicates removed (102) = 3926
- (3) Removed: Book and book section references (130) = 3796
- (4) Removed: abstract articles (40) = 3756
- (5) Removed: incomplete reference ex. author missing (115) = 3641
- (6) Excluded (1197):

a. Year before 2000 (168) = 3473 left

b. Duplicates on proceeding and journal articles (19) = 3454

c. Titles about city (20) = 3434

d. Titles about smart cities(12) = 3422

e. Child* (12) = 3410

f. Social media (43) = 3367

i. Tweet (9) = 3358

ii. Facebook(13) = 3345

iii. Youtube (7) = 3338

iv. Internet (47) = 3291 (articles containing "internet of things" were not removed)

v. web (205) = 3086

vi. twitter (18) = 3068

g. Biomedical (3) = 3065

h. Hand writing (14) = 3051

i. mobile data (8) = 3043

j. mobile application(17) = 3026

k. Spam (6) = 3020

l. Business (9) = 3011

m. Market (15) = 2996

n. Android(12) = 2984

o. Smartphone(58) = 2926

p. Phone(43) = 2883

q. Government(8) = 2875

r. Social network (77) = 2798

s. Vehicle(25) = 2773

t. Smart grid (17) = 2756

u. Game (47) = 2709

v. Password(9) = 2700

w. Banking(6) = 2694

x. Education or educational (18) = 2676

y. Student (12) = 2664

z. Mail (8) = 2656

aa. Word (12) as in keyword, word recognition or spotting = 2644

bb. TV (31) = 2613

cc. Television (5) = 2608

dd. Online (72) = 2536

ee. Shop or shopping (20) = 2516

ff. Virtual (45) = 2471

gg. Traffic (27) = 2444

- (7) Removed based on titles (2139) ex : gene, genetic, speech , cluster documents, AI on wall street, linguistic, anthropology , transducer, augmented environment, livestock monitoring, law enforcement, browsing(12), music (13), circuit, text recognition, user authentication, botanic, fraud, robot /smart house companion robot(26), clinical analysis, medical diagnosis, user's clicks/mouse activity, smartmeters, diabetes tracking, mobile devices, crime, augmented reality, pishing, fraud , Poster = 305
- (8) Full text articles assessed for eligibility = 305

a. Removed: workshop and posters and tutorials, smart metering /bill focus, /electricity focus and the like (154) = 151

A total of 151 articles are included in this literature review. In addition, 47 additional records identified through other sources were included:

- (1) 25 conceptual or seminal articles
- (2) 4 articles on legal challenges
- (3) 6 articles on ethical challenges
- (4) 13 articles recommended by expert sources

The total of articles included in this review are 198 articles.

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