University of South-Eastern Norway
Faculty of Technology, Natural Sciences and Maritime Studies

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Doctoral dissertation no. 63
2020

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Human Behaviour Modelling for Welfare Technology

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A PhD dissertation in
Process, Energy and Automation Engineering

Faculty of Technology, Natural Sciences and Maritime Studies
University of South-Eastern Norway
Porsgrunn, 2020

Doctoral dissertations at the University of South-Eastern Norway no.63

ISSN: 2535-5244 (print)
ISSN: 2535-5252 (online)

ISBN: 978-82-7206-548-4 (print)
ISBN: 978-82-7206-549-1 (online)

Print: University of South-Eastern Norway

Dedication

To Eliel and Gabriella

Preface

The present thesis has been submitted to the University of South-Eastern Norway (USN) in partial fulfilment of the requirement for the degree of Philosophiae Doctor (Ph.D.) in the Process, Energy and Automation Engineering program. This work has been performed at the Faculty of Technology, Natural Sciences and Maritime Sciences, in the Department of Electrical Engineering, Information Technology and Cybernetics. The research was conducted under the main supervision of Associate Professor Nils-Olav Skeie, and co-supervision of Professor Ola Marius Lysaker and Professor Carlos Pfeiffer.

This thesis represents the culmination of a three-year research in the technology field, with additional research in the health care field. The health care research was conducted in collaboration with Vice Dean Pia Cecilie Bing-Jonsson, Professor Grethe Eilertsen, and PhD student Ingrid Taylor at USN, and Assistant Professor Camilla Anker-Hansen at Østfold University College.

During the course of my research, I also participated in three international conferences, an advanced statistics and data mining summer programme in Madrid (2016), course work at the University of Agder and independent coursework at the University of Oslo.

Acknowledgements

I would first like to thank God and my parents, Digna and Edwin, for helping me to accomplish my dream of pursuing a Ph.D when I was 20 years old and just beginning my first MSc in Taiwan. I knew then that I wanted to pursue my education to the highest level in order to become a professor one day, and my parents have supported me throughout this journey. I am also thankful to my sister, Arelia, for reading my articles – even when you were busy and tired. I am also grateful to Tor Håvard Aasen for being there for me during the past four years, especially during the most difficult times of being a Ph.D. student. Without you, this journey would have been much harder.

To my friends Ingrid Taylor and Camilla Anker-Hansen, I cannot thank you both enough for being involved in my research. Both of you helped me to see research as fun even when it was demanding. Thanks also to my friend Michał Sposób for sharing the ups and downs of your Ph.D. life; I found relief in your stories.

I would also like to thank Professor Kaiying Wang for his support and counselling and Professor Knut E. Aasmundtveit for listening and giving me advice. Both of you provided support and guidance that made my PhD. possible. My thanks are also due to Professor Pia Cecilie Bing-Jonsson for stepping in and helping me during this Ph.D; I will always be thankful for all you have done. I am also grateful to Professor Grethe Eilertsen for collaborating with me and teaching me so much about research. You are a great example of what I hope to achieve in the future. Last but not least, I would like to give special thanks to my supervisors Nils-Olav Skeie and Marius Lysaker for helping me to achieve my PhD.

Abstract

Elderly populations are increasing in Norway, Scandinavia and other developed countries, in part because people are living longer due to medical advances. This is associated with several societal challenges, including an increasing demand for nursing homes, which may soon outstrip supply, and a projected nurse shortage. Moreover, some older people prefer to '*age in place*' – to stay in their own homes in safe and dignified living conditions for as long as they can take care of themselves – and welfare technology may help make this more possible.

The specific type of welfare technology researched in this thesis is in the area of human behaviour modelling (HBM) and represents a relatively new area of research. HBM seeks to model the behaviour of a person living alone in a smart environment in order to detect abnormal behaviour and alert family members or caretakers if something is wrong. It is based on an assumption that people tend to follow specific behavioural patterns in their daily lives. HBM should be tailored for each individual user since people have unique behaviour patterns. In the present thesis, a behaviour is defined as a combination of activity, posture, location and duration. Abnormal behaviours include, but are not limited to, falls and early signs of cognitive impairment.

This thesis analysed several algorithms to detect abnormal behaviour: decision trees, the hidden Markov model (HMM) and the hidden semi-Markov model. HBM has been developed and tested using a real-world, open-source dataset. The successful application to welfare technology requires consideration of a number of additional ethical and legal aspects. In addition, older people's attitudes towards welfare technology must be taken into account during the research and development phases to reduce the risk of rejection from its intended end-users and to ensure a person-centred approach to integrating new technology. This thesis therefore consists of two parts: a main technical part, which discusses the technological development of HBM, and a health care part, which discusses HBM's ethical and legal implications as well as older people's opinions about the use of HBM in welfare technology.

This thesis includes four Journal Articles and four Conference Articles. Overall, their results showed that it was possible to model an individual's behaviour and detect abnormalities using statistical models. The best results were obtained using HMM, which successfully detected abnormal behaviour such as falls, and changes in the duration of behaviours performed by an individual. In addition, the research examined opinions about the use of HBM for welfare technology among older people living in Norway. Most participants expressed that they wished to maintain their independence and autonomy, to feel safe in their own homes and to age in place, and they expressed positive opinions about the use of HBM and the great convenience it offered. Surprisingly, they expressed no concerns about privacy. Although a few mentioned concerns about loss of autonomy and dignity, most participants indicated that the potential benefits of HBM outweighed their concerns.

Keywords: ageing in place, ambient assisted living, assistive technology, behaviour modelling, healthcare, Norway, older people, pattern recognition, welfare technology,.

List of Articles

Journal Article 1

Sánchez, Veralia, Carlos Pfeiffer, and Nils-Olav Skeie. "A review of smart house analysis methods for assisting older people living alone." *Journal of Sensor and Actuator Networks* 6.3 (2017): 11. DOI: 10.3390/jsan6030011

Journal Article 2

Sánchez, Veralia, Ola Marius Lysaker, and Nils-Olav Skeie. "Human behaviour modelling for welfare technology using Hidden Markov models", *Pattern Recognition Letters* (2019). DOI: 10.1016/j.patrec.2019.09.022

Journal Article 3

Sánchez, Veralia Gabriela, Ingrid Taylor, and Pia Cecilie Bing-Jonsson. "Ethics of smart house welfare technology for older adults: a systematic literature review." *International Journal of technology assessment in health care* 33.6 (2017): 691-699. DOI: 10.1017/S0266462317000964

Journal Article 4

Sánchez, Veralia Gabriela, Camilla Anker-Hansen, Ingrid Taylor, Grethe Eilertsen, "Older People's Attitudes And Perspectives Of Welfare Technology In Norway", *Journal of Multidisciplinary Healthcare* (2019). DOI: 10.2147/JMDH.S219458

Conference Article 1

Pfeiffer, Carlos F., Veralia Gabriela Sánchez, and Nils-Olav Skeie. "A Discrete Event Oriented Framework for a Smart House Behavior Monitor System." *2016 12th International Conference on Intelligent Environments (IE)*. IEEE, 2016. DOI: 10.1109/IE.2016.26

Conference Article 2

Sánchez, Veralia Gabriela, Nils-Olav Skeie, "Decision Trees for Human Activity Recognition in Smart House Environments", *Proceedings of The 59th Conference on Simulation and*

Modelling (SIMS 59), 26-28 September 2018, Oslo Metropolitan University, Norway, Issue 153, 2018-11-19, Pages 222-229, ISSN 1650-3740. DOI: 10.3384/ecp18153222

Conference Article 3

Sánchez, Veralia Gabriela, and Carlos F. Pfeiffer. "Legal Aspects on Smart House Welfare Technology for Older People in Norway." 2016 12th International Conference on Intelligent Environments (Workshops). 2016. DOI: 10.3233/978-1-61499-690-3-125

Conference Article 4

Sánchez, Veralia Gabriela, "Welfare technology, healthcare, and behaviour modelling-an analysis." 16th International Workshop on Intelligent Environments: Supporting Healthcare and Well-being (Workshops). 2019. DOI: 10.3233/AISE190057

List of Tables

List of Figures

Abbreviations

AAL: Ambient assisted living

ADL: Activities of daily living

ACHE: The adaptive control of home environments

CASAS: The center for advanced studies in adaptive systems

HAR: Human activity recognition

HBM: Human behaviour modelling

HMM: Hidden Markov modell

HSMM: Hidden semi-Markov modell

HTA: Health technology assessment

MavHome: Managing an Intelligent Versatile Home

PRISMA: Preferred reporting items for systematic reviews and meta-analyses

WT: Welfare technology

Table of Contents

1 Introduction

This thesis proposes methods of human behaviour modelling (HBM), which is used to model the behaviours of older people who live alone. This section presents the study's aim, research questions, background, contributions, and structure.

1.1 Aim and Research Questions

This research sought to model the behaviours of older people living alone in order to detect abnormal behaviours and alert family members or caretakers when assistance was required. A person-centred approach is also considered by investigating the use of HBM in older people health care. This thesis is therefore comprised of two parts: a main technical part (Part I) a health care part (Part II).

The main research question (Part I) is as follows:

Is it possible to develop a model that can learn, recognise and predict an individual's behaviour patterns in order to detect abnormal behaviours?

Two sub-questions were formulated regarding the health care applications of such a model (Part II):

a. *What are the ethical and legal implications of applying such a model to health care?*
b. *What are potential users' attitudes towards such a model?*

These questions are investigated in a total of four Journal Articles and four Conference Articles, as shown in Figure 1. The main research question is examined in Journal Articles 1 [1] and 2 [2] and Conference Articles 1 [3] and 2 [4]. The sub-questions from part II are explored in Journal Articles 3 [5] and 4 [6] and Conference Article 3 [7]. Finally, Conference Article 4 [8] integrates both parts of this research.

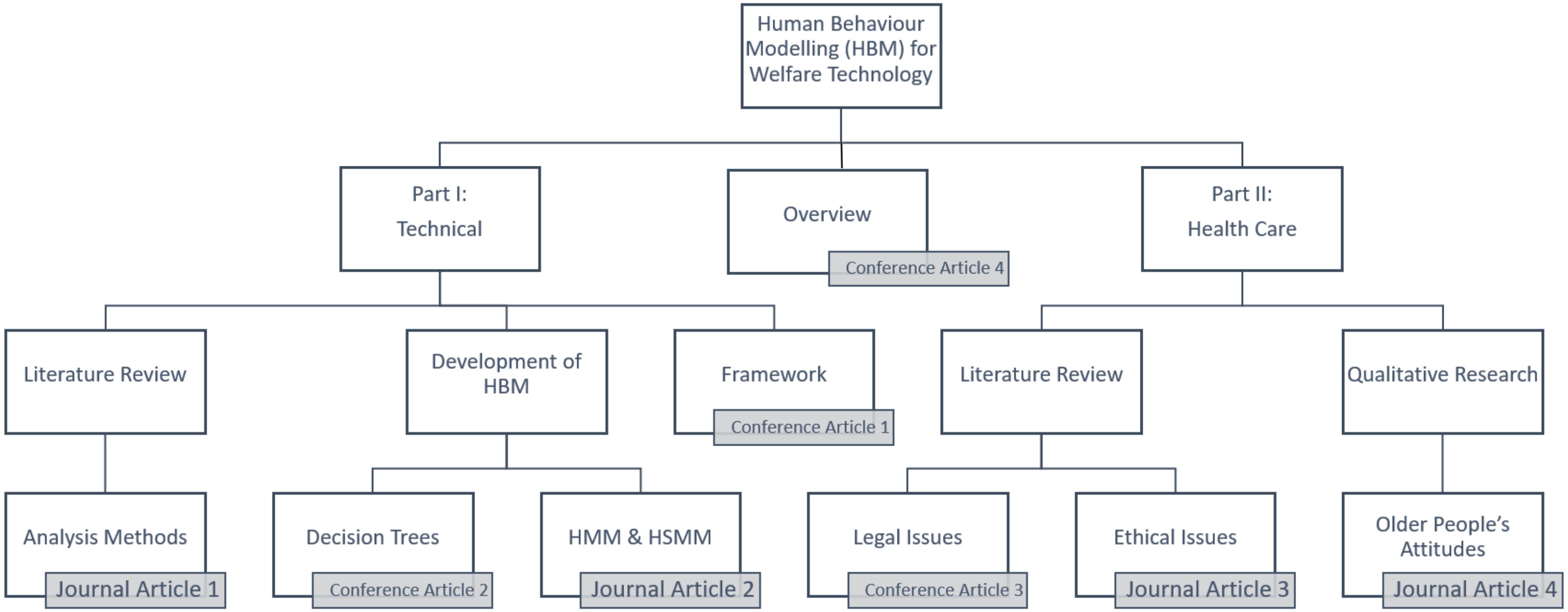

Figure 1. Overview of the Journal and Conference Articles.
HBM refers to Human Behaviour Modelling. HMM refers to Hidden Markov Models. HSMM refers to Hidden semi-Markov Models

1.2 Background and Purpose

Mortality rates among older populations have greatly decreased in recent decades in developed countries [9]. In the European Union, people aged 80 or older represented 5.5% of the population in 2017, and by 2080 this is expected to more than double, to 12.7% [10]. Although this represents successes in medical advances and health care, it is also associated with increasing health expenses in ageing societies [9].

Norwegian municipalities are responsible for providing care services to all residents, as regulated by the Norwegian Municipal Health and Care Service Act of 2011. Among the care services provided by municipalities are home health care, practical assistance with daily tasks and places in nursing homes for those who need it. However, only 50% of applications for nursing homes are handled within 15 days, with residents of big cities often having to wait longer to receive care than those living in less populated areas [11], and wait times can be a burden for an individual's family. In addition, there was a 2% reduction of available places in nursing and retirement homes between 2015 and 2018 [12].

In 2019, 38.5% of individuals aged 65 and older live alone in Norway [13], and in 2017, 32% of people aged 80 and over used home health care–based services [14]. The average cost of these home care services was approximately 227,000 kr (approximately €23,553) per person per year in 2013, while the cost of living in a nursing home was estimated at 900,000 kr per person per year (€93,393)[7], [15]. Moreover, 77% of applications for home health care were typically handled within 15 days [11]. These numbers suggest that while nursing homes are not able to cope with increased demand in Norway, home health care is still relatively accessible and cost-effective.

The sustainability of future health care services therefore requires that governments invest in *welfare technology* that can help older people remain in their homes for as long as they wish to and are able to take care of themselves [16]. Welfare technology, more often referred to as *ambient assisted living* outside of Scandinavia, is defined as 'technology used for environmental control, safety and well-being in particular for elderly and disabled people' [17, p. 335]. Moreover, with longer lives come greater expectations of maintaining good health while ageing [18]. Welfare technology therefore also seeks to improve the quality of life of those who use it. The opportunity for older people to stay in their own homes – i.e. to age in place – is not only a cost-effective way of coping with shortages of health care facilities and professionals, but also promotes independence, by allowing individuals to remain in familiar environments, and furthermore decreases individuals' risks of contracting infectious diseases [19], [20].

The main risks that older people face when living alone are safety-related, such as falls and dizziness [20], and welfare technology should therefore be able to mitigate these risks. Technology that can detect changes in a person's behaviour, such as falls, can support the creation of a safer environment for that person. The work presented here is based on the theory that people's daily activities and behaviours have discernible patterns [21], [22] that can allow for the detection of anomalies (i.e, patterns in the data that deviate from normal or expected individual behaviours) [23]. In this thesis, this type of welfare technology is referred to as HBM.

1.3 Contribution

This thesis contributes to the development of a model that can detect changes in the behaviours of a person living alone. Although several previous studies have sought to categorise human activities and behaviours [24]–[27], the identification of individual behaviours to detect abnormalities remains a largely unexplored topic. This thesis applies novel technical research to health care and reviews the ethical and legal implications of implementing welfare technology. Despite the potential advantages of applying welfare technology to ageing in place, several risks must be considered. The attitudes of older people towards welfare technology were also qualitatively explored, with the primary intention of taking older people's opinions into consideration at all stages of research and development, thus trying to maintain a person-centred approach.

1.4 Thesis Structure

The structure of this thesis is as follows. Chapter 2 provides an overview of the existing research on HBM and its legal and ethical implications. Chapter 3 introduces the theory underlying the research. Chapter 5 presents the dataset used in this thesis. Chapters 6 and chapter 7 summarise and discuss, respectively, the results of each Journal and Conference Article. Chapter 8 describes this research strengths and limitations, while Chapter 9 provides conclusions and directions for future work. Finally, the four Journal Articles and four Conference Articles are attached at the end of this thesis.

2 Research Status

This research began with literature reviews, which contributed to Journal Articles 1 [1] and 3 [5] and Conference Article 3 [7]. Part I, which is presented in detail in Journal Article 1 [1], consists of a literature review of the technical aspects of the research and reviews the analytical methods used to assist older people who live alone. Part II focuses on the health care implications of the technical research and is discussed in Journal Article 3 [5] and Conference Article 3 [7]. Journal Article 3 [5] is a systematic review of the ethics of using 'smart house' welfare technology for older people, and Conference Article 3 [7] reviews the legal implications of using smart house welfare technology for elder care in Norway. The rest of this chapter briefly summarises the existing research based on these three review Articles.

2.1 Part I: Technical Research

Generally, welfare technology applications for older people seek to improve their lives and safety [28]–[30] by learning individuals' activity patterns and adapting their homes to their needs [27]. The technique used to achieve this is usually called *human activity recognition* (HAR) [24], [25], [31] but may also be referred to as *activities of daily living* (ADL) recognition or detection [26], [32]. Both HAR and ADL recognition have the same aim of identifying an individual's activities, as detailed further in Journal Article 2 [2]. In this thesis, the more common term of HAR is used.

Studies involving HBM have not received the same kind of attention as HAR more broadly. This thesis therefore uses the knowledge derived from HAR's state-of-the-art techniques as a foundation for studying HBM. As described further in Journal Article 1 [1], machine learning and statistical algorithms are generally used to learn to predict an individual's activities. These algorithms include Bayesian methods, Markov chains, statistical inferential algorithms, neural networks, fuzzy logic and multi-agent system algorithms, among others.

Following are some prominent examples of prior research on the use of smart houses for welfare technology, using machine learning or statistical methods, which are documented in Journal Article 1 [1]. The Adaptive Control of Home Environments (ACHE) project at the University of Colorado seeks to achieve a home that can programme itself, using a neural network model that observes a person's lifestyle and desires and then learns to predict and adapt to their needs [33]. The Managing an Intelligent Versatile Home (MavHome) project at the University of Texas is based on the LeZi-update algorithm for tracking users and seeks to develop a home that functionally behaves as a 'rational agent' [34]. The GatorTech Smart House, developed at the University of Florida, is composed of several single smart devices connected to an operational platform, in order to optimise the comfort and safety of any older person [35].

Studies using decision trees in smart environments have also been successfully implemented [36], and one study that used decision trees achieved an 80% accuracy rate in recognising 20 everyday activities [37]. Similarly, decision trees were also used for activities recognition by Fan with good results [32]. Likewise, hidden Markov models (HMMs) have also been successful at recognising human actions. Since its first published application by Yamato et al. in 1992 [38], HMM has been used alone or in combination with other methods, such as neural networks and intelligent agents [39], [40]. For example, the Center for Advanced Studies in Adaptive Systems (CASAS) at Washington State University has used HMM with promising results in several residences in a smart house environment [41], while another study using HMM in a smart house achieved 98% accuracy in assisting individuals with diabetes [39]. Similarly, a project in the Netherlands used HMM to track a person for 28 days in a smart house environment and made the resultant annotated dataset available for public use [40]. These examples show that HMM and decision trees have both been successfully implemented for HAR [41]–[45]. Therefore, in this thesis, HMM and decision trees were both tested for use in HBM.

2.2 Part II: Health Care

The second part of this work focuses on the health care implications of HBM and its applications to welfare technology, with the goal of maintaining a person-centred approach. Person-centred approaches focus on the needs and values of the individual, which are central to health care practice and policy. These values include respect, autonomy, participation, justice, dignity, trust and patient safety and rights [46]. Some of the challenges of person-centred approaches deal with information and communication technology, including welfare technology. Literature reviews on the ethical and legal aspects of welfare technology were therefore conducted as a first step towards understanding some of the potential barriers to applying HBM to welfare technology. These are reviewed in more detail in Journal Article 3 [5] and Conference Article 3 [7], but a short summary is also provided here.

Saranummi et al. [44] noted that older people should have the right to live independently in their own homes for as long as they wish and should have access to assistance services. Understanding their needs is therefore a challenge to be addressed in the development of welfare technology. Nonetheless, the implementation of welfare technology, and particularly of smart houses, raises many ethical and legal concerns about privacy, autonomy, informed consent, dignity, safety, trust, legal obligations and stakeholders' interests and technology acceptance. Sadri [45] and Rozo [47] both noted that a major ethical challenge related to technology is that technical developers, rather than the end-users, typically establish anomaly detection. Similarly, the functions of a smart house welfare system are usually set by the developers [48]. This may lead to data being interpreted only from the developers' perspective, thereby limiting end-users' privacy and freedom of choice [45], [47].

Developers thus play a key role in welfare technology that can affect the end-users positively or negatively. Moreover, Detweiler et al. [48] argued that a gap exists between developers' values and the ethical implications of developing welfare technology for older people. In addition, potential users who are not involved in the research and development phases could ultimately reject the developed technology [47]. It is thus essential that developers take into consideration who the consumers are and what their needs might be [49]. Therefore, this thesis sought user feedback during the research and development stages to reduce the potential for errors in its final implementation of HBM [50].

3 Theory

This section explains the theory used throughout this thesis. First, the theory that underlies how HBM should work is explained. Second, it presents the contrasting definitions of activity and behaviour that are used in this thesis. Third, it describes the parameters of abnormal behaviours that were used in this research. Fourth, the theory of statistical versus machine learning is explained. Fifth, it presents the person-centred health care perspective. Lastly, the theoretical concepts behind some of the ethical perspective are described.

3.1 HBM

The HBM proposed in this thesis sought to detect abnormal behaviour in a smart house environment and alert family members or caretakers if assistance is needed. The idea is based on an assumption that people's tend to follow recognisable patterns in their daily lives [21], [22], rendering it possible to detect anomalies and provide assistance when needed. The model must be uniquely tailored to each individual, since different people can have different ways of living and different patterns in their daily lives. There must therefore be a learning period in which the model can learn an individual end-user's typical, normal behaviour; only afterwards should the model be ready to detect abnormal behaviour.

Figure 2 shows how HBM should work. Typically, a smart house will be equipped with different types of sensors, commonly including passive infrared, temperature, humidity, acoustic, pressure and distance sensors. Among the data that these sensors can gather are the position and movement of a person, as well as environmental variables of the house, such as temperature and humidity. These data are then stored in a database for further manipulation. Once the data are available, HAR is usually performed as described in section 2.1. In the present research, HBM is then implemented as an additional step beyond HAR. The data collected by smart house sensors are therefore used in this thesis for HBM.

Figure 2. Flow diagram of HBM. A number of studies have used data from smart house sensors to conduct HAR [21–26]; however, HBM has not yet received the same kind of research attention.

3.2 Activity Versus Behaviour

Journal Article 2 [2] details the definitions of activity and behaviour used in this thesis. Briefly, the term activity refers to peoples' actions, also often referred to as ADL . ADLs are formally defined as actions that 'require basic skills and focus on activities involved in taking care of one's own body' [51, p. 157]. These include sleeping, personal hygiene, showering, dressing, undressing, eating, etcetera. and form the basis of HAR [52] (see also section 2.1).

The definition of *behaviour* was chosen after reviewing different perspectives of its definition. According to Krause [53], a behavioural scientist , behaviour is the action, which is the result of an antecedent. An antecedent is the issue which precedes the action but is the root cause. According to the physiologist, Skinner [54], behaviour is explained in terms of stimulus, response, and consequences.

Usually, research focusing on behaviour modelling [55]–[57] within welfare technology do not state a proper definition on what a behaviour consists of. Nevertheless, it is possible to notice that most of these studies deal with the concept of context awareness. Journal Article 1 [1] includes the concept of context awareness, summarised in the next few lines. Context has been defined as 'the key for interaction without distraction' and that 'context describes features of the environment within which the activity takes place

' [58, pp. 588–589]. Furthermore, Schilit et al. [59] referred to context as location: where you are, who you are with, and what resources are close to you. Dey [60, p. 2] defined context as 'any information that can be used to characterise the situation of an entity'.

Therefore, using these concepts on context and using the definition of behaviour given by Krause [53] and physiologist Skinner [54] as foundations, the term *behaviour* in this thesis is defined as a combination of an activity type as well as its duration, its location, and the posture of the person who performs it (Figure 3). For example, having breakfast is a behaviour comprised of eating (activity), being in the kitchen (location), sitting (posture) and takes place within a given time span during the morning (duration).

The posture of the person is an important feature to consider given the fact that falls could be detected through this feature. The posture of the person could be sitting, lying, or standing. Thus, posture is included in in the *term behaviour* used in this thesis. The duration of the activities is also considered important because the person's normal behaviour can be modelled though it. For example, how long does the person usually spend sleeping?

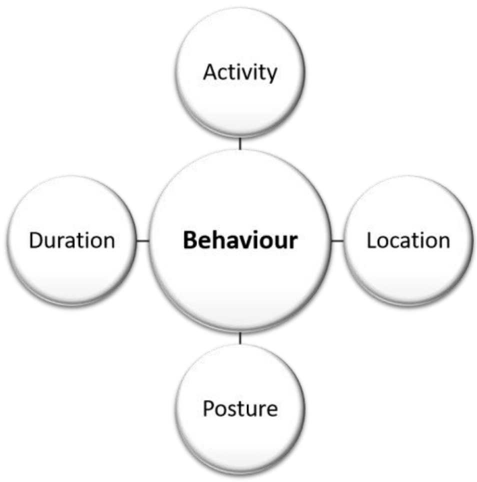

Figure 3. 'Behaviour' refers to an activity, its duration and its location, as well as the posture of the person performing it.

3.3 Abnormal Behaviour

Abnormal behaviour refers to behaviour that does not follow an individual's usual behavioural patterns. Abnormal behaviour falls under the category of anomaly detection, which is defined as 'the problem of finding patterns in data that do not conform to expected behaviour' [61, p. 1]. Anomaly is also called an 'outlier' in many mathematical and statistical disciplines [62], or an 'abnormality' or 'deviant'. Hawkins [63, p. 1] formally defined an anomaly as 'an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism'. For example, an HBM could learn during its training period that a specific individual's normal behaviour pattern consisted of waking up around 2 am, going to the bathroom for less than 10 minutes and then going back to sleep. If the individual woke up around 2 am and then spent more than 10 minutes in the bathroom and did not return to sleep, this would constitute an abnormal behaviour that could indicate a possible accident in the bathroom, thereby triggering an alarm. Likewise, if the HBM registered a behaviour that had never previously occurred, such as leaving the house at 2 am, this new scenario would also be classified as abnormal behaviour and should trigger an alarm.

3.4 Statistical Versus Machine Learning

In order to develop HBM, several statistical and machine learning algorithms were considered and reviewed, as described in Journal Article 1 [1]. Ultimately, statistical algorithms were chosen to develop HBM, primarily due to the size of the dataset and the fact that machine learning algorithms generally require abnormal behaviour to have been trained a priori (cf. Journal Article 2 [2]). In addition, machine learning techniques typically require large quantities of data for training, and classic statistical methods tend to be more effective with smaller datasets [64]. A statistical approach therefore tends to perform better for behaviour pattern recognition within smart houses, since the datasets are usually small and it is difficult to access large relevant datasets [52]; there are challenges associated with finding study participants who are willing to live in a smart house designed to collect data for research, as well as a number of ethical considerations that must be taken into account (cf. Journal Article 3 [5]). Participants and researchers would also then have to verify that the collected data are accurate and label the behaviours accordingly. Moreover, an individual's behavioural anomalies cannot, as of yet, be learned a priori from the currently available data. The publicly available datasets typically consist of a single person living alone for only a few days or months while performing his or her ADLs [52]; they do not contain any abnormal behaviours in their patterns. Therefore, in this work, a fictional dataset with abnormal behaviour was created to test the model, in conjunction with data from a small open-source dataset.

3.5 Person-centred Care

In this section, the theory of person-centred care is presented since a person-centred care perspective was tried to keep in mind when developing HBM. Person-centred research focuses on the necessity of respecting the individual, which in this study refers to older persons [65]. As mentioned in Section 2.2, person-centred care emphasises the needs and values of the individual, such as respect, autonomy, participation, justice, dignity, trust, and patient safety and rights [46]. Person-centred care has gained a lot of attention lately. For example, the University of South-Eastern Norway opened a PhD program in person-centred health care in 2014.

Person-centred care has been defined by McCormack and McCance [66, p. 3] as:

An approach to practice established through the formation and fostering of healthful relationships between all care providers, service users and others significant to them in their lives. It is underpinned by values of respect for persons (personhood), individual right to self-determination, mutual respect and understanding. It is enabled by cultures of empowerment that foster continuous approaches to practice development.

This definition shows the complexity of person-centredness. McCormack and McCance [66] developed a framework through empirical research spanning over 20 years. The framework focuses on person-centred practice involving older people and the experiences of caring in nursing practice as well as healthcare policies and professional practice worldwide [67]–[69]. Furthermore, it is based on the principle level because there are no tools, procedures, nor methods that can be transferred to every context [66].

The person-centred practice framework consists of five domains: macrocontext, prerequisites, care environment, person-centred processes, and person-centred outcomes [66]. The goal of the framework is based on the philosophical foundations of being person-centred towards an individual no matter the type of health problem [67]. Therefore, in order to keep the individual's value central in this research, interviews were conducted with the main aim of considering older people's attitudes and experiences towards welfare technology, which is in line with the person-centred perspective.

3.6 Ethical Perspectives

Continuing with the person-centred care perspective of focusing on the values of the individual, the theory of four of the major recurring values as well as ethical challenges found in Journal Article 3 [5] are summarised. These are autonomy, informed consent, dignity, and trust. This section is not meant to provide new definitions, but rather an overview of their meaning.

3.6.1 Autonomy

Autonomy has been defined by dictionaries as the quality or state of being self-governing, self-directing, or even independent [70], [71]. However, autonomy has deeper roots in philosophy. According to Feinberg [72], within moral and political philosophy, autonomy has at least four different meanings. These are the capacity to govern oneself, the actual condition of self-government, a personal ideal, and a set of rights expressive of one's sovereignty over oneself. In several moral frameworks, autonomy plays a central role, such as in Kantian's view on universal moral law.

Dworking [73] states that autonomy refers to the states of a person. Other philosophers refer to autonomy as the power to make one's desires effective [74], [75]. Moreover, autonomy may carry legal implications [74]. The European human rights framework considers autonomy in the construction of one's identity [76].

These definitions demonstrate how important autonomy is for an individual. Therefore, the individual's autonomy should always be respected when developing welfare technology. Welfare technology should respect and allow individuals to be their own persons and to be able to choose how to live their lives according to their own motives, desires, and conditions.

3.6.2 Dignity

The concept of dignity is complex. Several researches reviewed in Journal article 3 [5] have included the topic of dignity without providing a formal definition [49],[77]. One reason for this might be that dignity is not a concept that can be easily defined. Some researchers have even argued that the concept of dignity is ambiguous and thus cannot be discussed as an ethical concept [78]–[80].

However, Sulmasy [81] has refuted those claims by proposing three categories of the word dignity. These categories are intrinsic, attributed, and inflorescent, wherein dignity refers to the worth, stature, or value of the human being [81]. This concept of dignity is similar to the one used by the dictionary, where dignity is defined as 'the quality or state of being worthy, honoured, or esteemed' [82]. Another study considering Thomas Aquinas's Summa Theologiae, related dignity to the concept of virtue [83].

Therefore, according to these studies, dignity comprises the worth, value, and virtue of the person. As studied in Journal article 3 [5] and Journal Article 4 [6], dignity in welfare technology was understood within this scope.

3.6.3 Trust

According to epistemology, trust deals with the question, 'Should I trust or should I not trust?' [84], [85] . The question by itself demands a person to be conscious and aware that trusting can lead to problems or risks. In the same line of thought, a study defined technological trust as 'a person's belief that a tool or technology will not fail' [86, p. 754]. Therefore, if the person distrusts technology, this could lead to resistance.

According to some researchers, factors such as social role, politics, or beliefs can influence the trust of a person or institution [87]. Others claim that in order to trust, individuals must rely on the reputation of a person or an institution [88]. Hence, trust means believing that something or someone is reliable, safe, and will not cause harm, and welfare technology should provide this trust.

3.6.4 Informed consent

Conference Article 3 [7] described the major components of informed consent as competence, disclosure, understanding, and voluntary understanding. A study by Demiris stated that informed consent was 'an individual's autonomous authorisation of a clinical intervention or research participation' [89, p. 110]. Regarding the definition of the European Parliament, it states that the consent of a person 'may be given by any appropriate method enabling a freely given specific and informed indication of the user's wishes' [90, Para. 17].

Informed consent could be regarded as protection for an individual who is competent to give authorisation; in this case, it is authorisation to use welfare technology. Therefore, the person should be able to understand the benefits and risk that welfare technology brings. In addition, the person should agree voluntarily to use welfare technology.

4 Methodology

In this section, the methodology used for developing the HBM is briefly presented first. These are decision trees, HMM and Hidden semi-Markov Models (HSMM). Then, the methodology underlying the qualitative research methods used in Journal Article 4 [6] is described.

4.1 HBM Methods

The idea of HBM is to detect whether the behaviour of the person is normal or abnormal. Hence, using classification algorithms for HBM could provide optimal results. Figure 4 depicts the schematic of a classification algorithm. The data used for classification consist of a collection of records characterised by the tuple *(x,y)*. *x* describes the record, and *y* is the class label for the record. The task of the classification model is to represent the relationship between the attribute set (x) and class label (y) [91]. In this thesis, the output would be normal or abnormal behaviour.

Figure 4: Schematic of a classification task

Journal Article 1 [1] reviews the algorithms for potential use in developing the HBM. Ultimately, three statistical algorithms for classification were chosen because of their strong HAR results: decision trees, HMMs, and HSMMs.

The program MATLAB was used for implementing decision trees. MATLAB and Java was used for HMMs. Finally, the program R was used for implementing HSMMs.

4.1.1 Decision Trees

Decision Trees are a well-known classification algorithm and thus it is the first algorithm used for HBM. As described in more detail in Conference Article 1 [4], decision trees, also known as classification and regression trees, are a hierarchical model that can use existing data to predict responses. In essence, decision trees seek to predict the value of an output variable based on the input variables.

4.1.2 HMM

The second algorithm used is HMM, which is also a type of classification algorithm. HMM advantage is that it can deal with more complex data, including the capacity of dealing with independent and hidden variables [91]. As described further in Journal Article 2 [2], HMMs are a 'subclass of Bayesian networks known as dynamic Bayesian networks' [92, p. 15]. HMMs were used in this research because they perform well with small datasets with insufficient training data [93], [94]. In addition, HMMs are generative probabilistic models that can be used to generate hidden states from observable data, which was relevant since the focus of this work was on learning to recognise and decode individuals' behaviours.

4.1.3 HSMM

HSMM is the last algorithm used for HBM in this thesis. The theory underlying HSMMs is also detailed in Journal Article 2 [2]. In short, HMM major weakness is the state duration [93]. HSMMs aims to solve this problem by introducing a sojourn time for each state. HSMMs are an extension of HMMs that additionally include duration. HSMMs allow 'the underlying process to be a semi-Markov chain with a variable duration or sojourn time for each state' [94, p. 216]. As a result, an HSMM's parameters are the same as an HMM's, with the sole addition of a sojourn time for each state.

The purpose of using HSMMs in this research is that the HBM proposed in this thesis uses the *duration* of each activity as a parameter to determine normal and abnormal behaviour. Therefore, HSMM would help to explicitly introduce the duration of each activity during the learning phase.

4.2 Qualitative Research

Qualitative research methods were used to conduct interviews with older people (cf. Journal Article 4 [6]) to gain insights into their attitudes and perspectives towards welfare technology. Qualitative research is used to further understand a complex or new phenomenon that is barely understood [95]. HBM welfare technology (the phenomenon) is relatively new, and thus older people's attitudes towards it is paramount. The main purpose of doing qualitative research in this thesis was to maintain a person-centred approach by including the older people's opinions in the research and its development stage.

Qualitative research methods are commonly used to interpret interview data, which must be reliably interpreted and coded by researchers [96]. As noted by Moretti et al. [96], a major advantage of qualitative research is the richness of its data. The general goal of qualitative content analysis is to interpret subjective data in a scientific manner [96].

4.2.1 Recruitment Process

A sample was recruited from two counties in Norway. The recruitment process was challenging as it was difficult to find participants. Therefore, two recruitment techniques were used. Firstly, criteria sampling was used; in this approach, the participants are selected according to predetermined inclusion criteria [97]. This inclusion criteria was living alone; being older than 75 years old; speaking Norwegian, English, or Spanish; and not receiving any kind of public healthcare services.

Due to the slow recruitment process, snowball sampling was used as a second recruitment technique. Snowball sampling involves asking knowledgeable people about whom could participate. Patton described snowball sampling as a method whereby 'asking a number of people who else to talk with, the snowball gets bigger and bigger as you accumulate new information-rich cases' [97, p. 56].

Nine participants were recruited in total from May 2017 to January 2018. The demographic characteristics are depicted in Table 1. Each of the participants contributed to interesting and distinctive narratives on their experiences of living alone and attitudes towards welfare technology.

Table 1: Demographic characteristic of participants [6].

Participant	Gender	Age	Civil status	Type of house	Years living alone	Years in current house
P1	Female	91	widow	Senior apartment	no data	22 years
P2	Male	79	widow	Own house	2 years	49 years
P3	Male	80	widow	Senior apartment	6 years	2 years
P4	Male	79	widow	Own house	14 years	14 years
P5	Male	79	widow	Own house	1.5 years	No data
P6	Female	83	divorced	Own house	60 years	13 years
P7	Female	84	widow	Apartment	11 years	20 years
P8	Female	84	widow	Own house	10 years	52 years
P9	Female	89	widow	Senior apartment	16 years	7 years

4.2.2 Data Collection and Analysis

The HBM research project was explained to the participants at the beginning of the interviews. It is worth noting that the participants did not have experience with HBM, since it is still in the research stage. However, several of the participants had the experience of using technology as a means to make their lives easier and safer. For example, carrying mobile phones at all times to call for help, having an emergency number on speed dial, using fall alarms, or even having fall safety alarm systems installed in their own homes.

A semistructured interview guide was developed, and details of it can be found on Journal Article 4 [6]. In short, three broad themes of inquiry were investigated: 1) reflections on safety issues, 2) experiences with and attitudes towards welfare technology, and 3) experiences with and attitudes towards privacy issues.

Two of the co-authors of Journal Article 4 [6], who are Norwegian, conducted the interviews in the Norwegian language, but the author of this thesis was present in eight of the interviews. Conducting the interviews in Norwegian allowed the participants the possibility of expressing themselves better in their native language. Nevertheless, the author of this thesis was able to clarify any doubts about the HBM throughout the interview. The interviews followed a conversation style, which appeared quite suitable for the participants. There was an easy flow of information from the participants as they narrated their histories.

The interviews ranged from 45 to 75 min in length and were recorded with consent from the participants. Only one interview was not recorded upon request of the participant; however, field notes were taken. The recorded interviews were transcribed for further analysis.

The qualitative analysis method described by Graneheim and Lundman [98] was used here. This method would enable the classification of collected data into meaning units, codes, subcategories, categories and themes which can then be discussed. Meaning units refer to words, sentences or paragraphs that address the same topic. Codes are labels assigned to the condensed meaning units. Subcategories are groups of codes that share similarities; they are grouped under categories that reflect their broader similarities. Finally, theme refers to the overall interpretive thread of the research conveyed through the condensed meaning units, codes, subcategories and categories [98].

For the analysis, one interview was randomly selected for initial analysis by all the authors. After discussing the preliminary analysis, the rest of the interviews were analysed by the author of this thesis following the same procedure. The analysis identified meaning units, which were then condensed and codified, followed by preliminary suggestions of subcategories. The analysis was extensive, and several discussions were held with all the co-authors of Journal Article 4 [6]. The analysis process took several months until unanimous consent from all the authors was achieved. An example of the analysis process is depicted in Table 2 (this table is also in Journal Article 4 [6]). The final analysis consisted of 615 meaning units, 52 codes, 4 subcategories, and 2 categories.

Table 2: Example of the analysis procedure from a manifest to a latent level [6].

Manifest level		Latent level		
Meaning Units	**Condensed meaning unit**	**Code**	**Sub-categories**	**Categories**
There is a nurse that comes just to deliver pills to my neighbour four times a day, it is not nice, but it is worse to have a machine for that	Home care nurse delivering pills is better than technology	Technology care should not replace human care	Concerns and dilemmas	Preferences and concerns of welfare technology
I am very careful, I always have my mobile in my night table and with me, even when I go to the bathroom in the night just in case I could fall or anything happens	Carrying phone to be able to call in case of emergency or falling	Having an action plan in case of emergency	Facing own ageing-preparedness for unpredictable scenarios	Reflections of today and tomorrow-awareness of own health

Qualitative research can be challenging since it relies to some extent on subjective interpretations [98] in which 'data and interpretation are co-creations of the interviewee and the interviewer and interpretation during the analysis phase is a co-creation of the researchers and the text' [99, p. 29]. As a result, several possible interpretations may be possible for any given datum, and researchers must maintain trustworthiness in their interpretations. As further described in Journal Article 4 [6], this research used the trustworthiness criteria established by Lincoln and Guba [100], which consist of credibility, transferability, dependability, and confirmability.

4.2.3 Ethical Considerations

The study was reported to the Norwegian Center for Research Data (NSD, project number 53841). It is worth noting that NSD does not approves projects but they must be notified about the processing of personal data in the project [101]. Participation in the research was voluntary, and no economic compensation was provided.

At the beginning of the interviews, all the participants received verbal and written information about the project. They were assured that their personal information would remain anonymous and confidential. The interviews were audio recorded, and the transcripts were de-identified. This means that the transcripts did not contain any names, addresses, family names, or any other personal information that could identify the participants.

Eight participants signed an informed consent form to participate in the study. One participant declined to sign and be audio recorded. Unfortunately, it was not possible to find out the reason since the participants replied ‘we will not talk about it’ when questioned. Nevertheless, the participant gave oral informed consent. After this particular interview, NSD was contacted to confirm if the data collected from this participant could be used. NSD clarified that as long as oral informed consent was given, it was possible to use the collected data.

5 Dataset

This section describes the dataset used to develop HBM, explains how the data were handled and describes the fictional dataset created to test the model.

5.1 Dataset Description

The data used in this thesis came from an open-source, real-world dataset named '*Activities of Daily Living (ADLs) Recognition Using Binary Sensors Data Set*', which is available for public download at University of California Irvine Machine Learning Repository [102]. An open-source dataset was chosen in order to obtain unbiased results. In addition, this dataset uses real-world data and has been used in other research [103]. It consists of data about the ADLs of two people living independently in their own homes, and is comprised of one set of data spanning 14 days (*OrdonezA*) and one set of data spanning 21 days (*OrdonezB*), corresponding to two people, A and B. The datasets are provided in a text file format. The properties for *OrdonezA* are depicted in Table 3.

Table 3. Attributes of the OrdonezA dataset used in this thesis [49]. ADLs refers to activities of daily living. PIR refers to passive infrared.

Name	Value
Setting	Apartment
Number of locations	4 Rooms and hall/entrance
Number of labelled days	14 days
Labels (ADLs included)	Leaving, Toileting (Personal hygiene),Showering, Sleeping, Breakfast, Lunch, Dinner, Snack, Spare time/TV, Grooming
Number of sensors	12 sensors
Sensors	PIR: Shower, Basin, Cooktop Magnetic: Main door, Fridge,Cabinet, Cupboard Flush: Toilet Pressure: Seat, Bed Electric: Microwave, Toaster

In order to avoid confusion, this thesis uses the same terminology as the dataset. Therefore, for example, the term 'toileting' is used instead of 'personal hygiene'. All activities were manually labelled by the two participants A and B. Both datasets were used to help develop the HBM, as described further in Journal Article 2 [2] and Conference Article 2 [4].

5.2 Data Handling Procedures

The data handling procedures described here were applied in the development of the HBM using decision trees, HMM and HSMM, as described in Conference Article 2 [4] and Journal Article 2 [2], respectively. The datasets are publicly available as a text file, which for the purposes of the present research was imported directly into MATLAB.

The first step in developing HBM is to learn an individual's behaviour patterns over a period of time and identify repetitive patterns; this is known as the training period. The goal of the training period is to define an individual's normal behaviours and predict future behaviours. The second step is to test the model and determine its accuracy. For *OrdonezA*, 7 days of data were used to train the model and another 7 days were used to test it. For *OrdonezB*, 14 days were used for training and 7 days were used for testing. In order to verify if the model detected abnormal behaviour, a fictional dataset with abnormal behaviour was also created, as described in the next section and in Journal Article 2 [2]. A sample day of the *OrdonezA* dataset is shown in Table 4.

Table 4. 'Day 1' in the OrdonezA dataset. The dataset includes the date, start time, end time, activity and location.

Date	*Start Time*	*End Time*	*Activity*	*Location*
28-11-11	02:27:59	10:18:11	Sleeping	Bedroom
28-11-11	10:21:24	10:23:36	Toileting	Bathroom
28-11-11	10:25:44	10:33:00	Showering	Bathroom
28-11-11	10:34:23	10:43:00	Breakfast	Kitchen
28-11-11	10:49:48	10:51:13	Grooming	Bathroom
28-11-11	10:51:41	13:05:07	Spare time/TV	Living room
28-11-11	13:06:04	13:06:31	Toileting	Bathroom
28-11-11	13:09:31	13:29:09	Leaving	Hall
28-11-11	13:38:40	14:21:40	Spare time/TV	Living room
28-11-11	14:22:38	14:27:07	Toileting	Bathroom
28-11-11	14:27:11	15:04:00	Lunch	Kitchen
28-11-11	15:04:59	15:06:29	Grooming	Bathroom
28-11-11	15:07:01	20:20:00	Spare time/TV	Living room
28-11-11	20:20:55	20:20:59	Snack	Kitchen
28-11-11	20:21:15	02:06:00	Spare time/TV	Living room

Ideally, the data should also specify the *posture* of the individual. However, this information was not available in this dataset, and an additional column for *posture* was therefore added. The possible values for posture were *lying*, *sitting* and *standing*. For the present research, a posture was assigned to each activity according to the most typical posture of a person performing that activity (e.g. 'lying' during a 'sleeping' activity). Each posture value was then coded as a number in order to develop the MATLAB code (Table 5). A total of 10 activities, 5 locations and 3 postures were used.

Table 5. Assigned number values and postures associated with specific activities.

Number	*Posture*	*Allowed Activity*
1	Lying	Sleeping, Spare time
2	Sitting	Toileting, Breakfast, Spare time, Snack, Lunch, Dinner
3	Standing	Showering, Grooming, Leaving

5.3 Fictional Dataset

A fictional dataset was created to test the models because the Ordonez datasets did not contain any instances of abnormal behaviours. A fictional dataset containing examples of abnormal behaviours was therefore necessary to test whether the models could detect behaviours that deviated from the normal patterns present in the Ordonez datasets. Although some simulators to generate data have been previously created [52], [104], including at USN [105], due to time limitations it was not possible to generate a full simulated dataset for this thesis.

The manual creation of a fictional dataset is described in more detail in Journal Article 2 [2], but briefly, the fictional dataset was comprised of 3 days of data that included some deviations in the durations, postures and sequences of normal activities. For example, the durations of some of the activities were exaggerated, and on day 1 the posture for the activity 'leaving' at the location 'entrance' was changed to 'lying', to simulate a fall. Day 2 also contains a change in the posture for the activity 'sleeping', which was changed to 'standing'. Finally, the sequence of activities on day 3 was changed. The fictional dataset is shown in Table 6.

Table 6. Fictional dataset.

Date	*Start Time*	*End Time*	*Posture*	*Activity*	*Location*
Day 1	2:27:59	10:18:11	Lying	Sleeping	Bedroom
Day 1	10:21:24	10:23:36	Sitting	Toileting	Bathroom
Day 1	10:25:44	10:33:00	Standing	Showering	Bathroom
Day 1	10:34:23	10:43:00	Sitting	Breakfast	Kitchen
Day 1	10:49:48	10:51:13	Standing	Grooming	Bathroom
Day 1	10:51:41	13:05:07	Sitting	Spare time/TV	Living room
Day 1	13:06:04	13:06:31	Sitting	Toileting	Bathroom
Day 1	10:49:48	10:51:13	Standing	Grooming	Bathroom
Day 1	10:51:41	13:05:07	Standing	Spare time/TV	Living room
Day 1	13:06:04	13:06:31	Standing	Toileting	Bathroom
Day 1	13:09:31	13:29:09	Lying	Leaving	Hall
Day 2	1:01:05	8:20:10	Standing	Sleeping	Bedroom
Day 2	8:20:15	8:25:52	Sitting	Toileting	Bathroom
Day 2	8:26:02	8:29:26	Standing	Grooming	Bathroom
Day 2	8:30:41	8:45:03	Standing	Showering	Bathroom
Day 2	8:55:16	9:20:56	Sitting	Breakfast	Kitchen
Day 2	9:22:32	11:15:31	Lying	Spare time/TV	Living room
Day 2	11:18:01	11:22:25	Sitting	Toileting	Bathroom
Day 2	11:22:58	11:24:34	Standing	Grooming	Bathroom
Day 2	11:25:54	12:35:10	Sitting	Spare time/TV	Living room
Day 2	12:36:21	12:53:15	Sitting	Lunch	Kitchen
Day 2	12:54:14	12:57:25	Sitting	Toileting	Bathroom
Day 2	12:58:00	13:01:01	Standing	Grooming	Bathroom
Day 2	13:02:11	18:54:02	Standing	Leaving	Hall
Day 3	1:40:12	9:14:56	Lying	Sleeping	Bedroom
Day 3	9:15:16	9:35:26	Sitting	Breakfast	Kitchen
Day 3	9:36:01	9:50:52	Sitting	Toileting	Bathroom
Day 3	9:51:45	10:21:43	Standing	Showering	Bathroom
Day 3	10:22:34	10:27:25	Sitting	Toileting	Bathroom
Day 3	10:27:35	10:29:11	Standing	Grooming	Bathroom
Day 3	10:30:03	12:15:41	Sitting	Spare time/TV	Living room
Day 3	12:16:14	12:24:10	Standing	Grooming	Bathroom
Day 3	12:24:54	19:14:41	Standing	Leaving	Hall

6 Article Summaries

This section summarises the purpose and contributions of the appended Journal and Conference Articles to provide an overview of this thesis. The results are divided into two parts: technical research and health care research. The technical part, which is comprised of two Journal Articles and two Conferences Articles, describes the development of the HBM, as depicted in Figure 5. An initial framework of the behaviour monitoring system is presented in Conference Article 1 [3], while Journal Article 1 [1] provides a literature review. Three algorithms were then investigated for development of the HBM: decision trees (Conference Article 2 [4]), HMM and HSMM (Journal Article 2 [2]).

Some explorations of the health care applications and implications of HBM complement the technical research and are discussed in two Journal Articles and one Conference Article (Figure 7). Conference Article 3 discusses the legal aspects, Journal Article 3 [5] investigates the ethical aspects and Journal Article 4 [6] investigates older people' attitudes towards the use of HBM for welfare technology. Finally, Conference Article 4 [8] provides an overview that connects the technical and health care facets of this thesis's research on the use of HBM in welfare technology.

6.1 Part I: Technical Research

The Articles presented here focus on the technical aspects of the research conducted for this thesis (Figure 5).

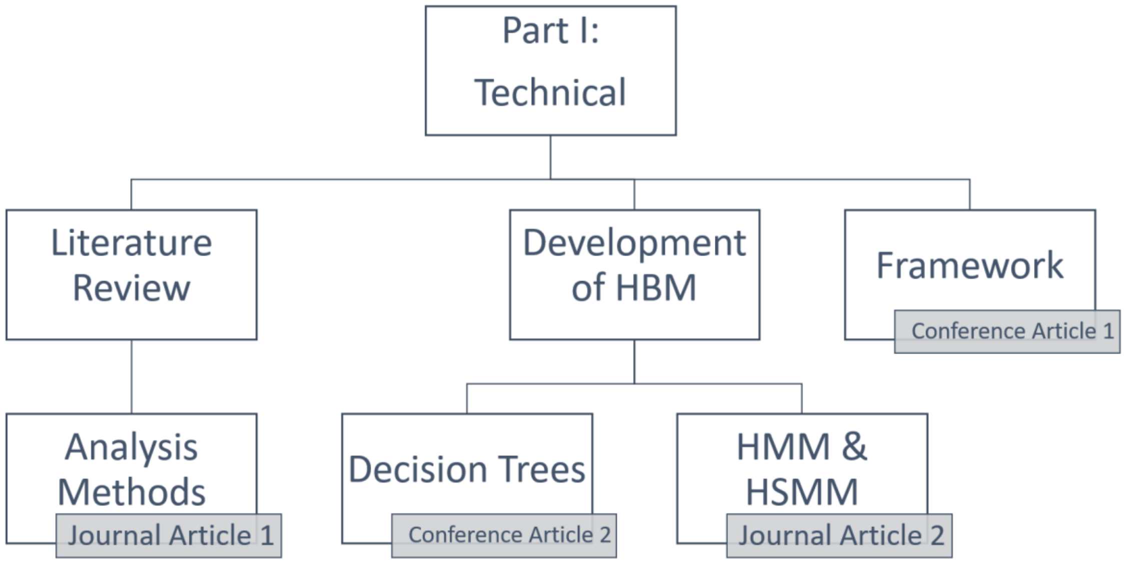

Figure 5. Overview of the technical Journal and Conference Articles. HBM refers to Human Behaviour Modelling. HMM refers to Hidden Markov Models. HSMM refers to Hidden semi-Markov Models.

6.1.1 Conference Article 1

A Discrete Event-Oriented Framework for a Smart House Behaviour Monitoring System

The first Conference Article focused on the theory underlying the construction of a behaviour monitoring system. The idea was to build a non-invasive system that could help evaluate the activities and behaviours of people living alone; 'non-invasive' refers to the fact that no wearable devices of any kind were to be used and individuals should not be asked to change their daily routines in any way. The Article classified how normal or abnormal behaviour should function in the model. Abnormal behaviour could range from falls to cognitive impairment, such as early signs of dementia. Other abnormal behaviour could be configured a priori – for example, not getting out of bed, skipping meals, leaving the house in the middle of the night, etc.

It should be noted that since this was the first study conducted for this thesis, some of its terminology differs from that used in later Articles, and several of the terms and definitions used in the published version of this Conference Article are not used in this thesis. Instead, this thesis uses the definitions given in section 3.2 and the terms defined in the Appendix. Moreover, after careful consideration and further research, the event-based approach depicted in this Conference Article 1 was discarded.

6.1.2 Journal Article 1

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

The first step towards developing a model that could detect changes in individual behaviours was to research the current state-of-the-art methods. Research on human behaviour is a relatively new field, so the emphasis in this Article was on reviewing the analysis methods that are most commonly used to assist older people who live alone. A total of 198 articles were included in this literature review. The literature review showed that several methods have been previously implemented to optimise the learning processes of HAR in smart house environments. The reviewed algorithms were divided into three main categories: computer vision and pattern recognition, artificial intelligence and Markov models. Their results were carefully reviewed and three statistical algorithms with promising results in activity recognition were ultimately selected as the bases from which to develop HBM in the present thesis: decision trees, HMM and HSMM. All three of these algorithms were then tested as possible methods of modelling the behaviours of an individual in a smart house environment; their results are described Conference Article 2 [4] and Journal Article 2 [2].

6.1.3 Conference Article 2

Decision Trees for Human Activity Recognition Modelling in Smart House Environments

Decision trees were the first algorithm tested for HBM. Decision trees are a hierarchical model that can use data to predict responses. This method was the first one tested because its implementation is straightforward and would provide for a quicker development of HBM than any of the other considered algorithms.

To test decision trees' accuracy in HBM, *activity* recognition was implemented first; *behaviours* were then constructed using the 'duration' and 'position' values. Decision trees were able to correctly classify seven out of the nine activities in the dataset. Most of the behaviour mispredictions happened with activities performed in the same location – for example, confusion between showering and grooming, which both took place in the bathroom, or between breakfast, lunch and snack, which were all performed in the kitchen. Nevertheless, the overall success rate for activity recognition was very high, at approximately 88%.

However, since decision trees are a probabilistic algorithm, they can create some errors in prediction tasks, and they will always choose the response with the highest probability according to their training. Ultimately, therefore, while decision trees proved to be a good tool for activity recognition, they were determined to be insufficiently precise for HBM.

6.1.4 Journal Article 2

Human behaviour modelling for welfare technology using Hidden Markov models

Journal Article 2 [2] examined the second algorithm tested for HBM, HMM, which has reportedly been successful in previous HAR research [39], [41]. HMM also has the advantage of working well with small datasets and insufficient data [93]. The present research therefore sought to determine whether HMM could accurately predict whether a given behaviour was normal or abnormal. Using the dataset as described in Section 5.1, the HMM was trained using an individual's *location* as an observable variable and their *activity* as the hidden variable. Subsequently, the individual's *posture* was checked using a Boolean method and the *duration* of the specified behaviour was checked using time rules. Finally, the individual's *behaviour* was classified as normal or abnormal. Figure 6 shows the flow diagram of this methodology, which was used in Journal Article 2 [2].

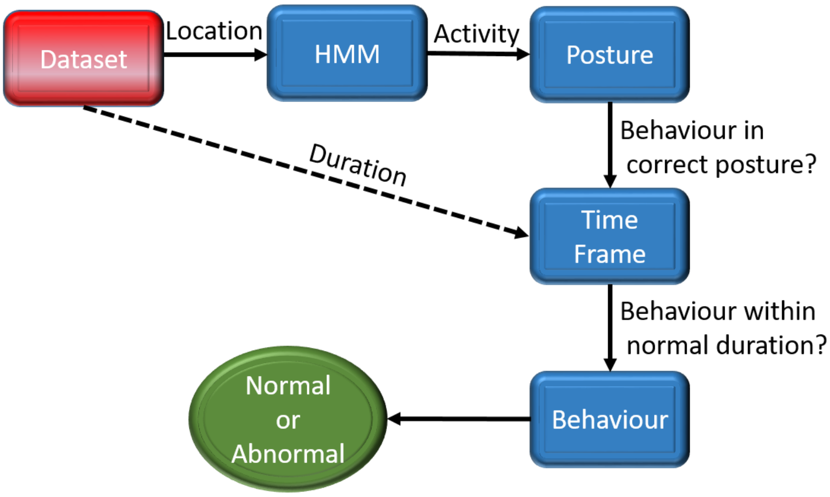

Figure 6. Flow diagram of the HMM methodology proposed for use in HBM. Figure also reported in Journal Article 2[2].

The prediction accuracy of the HMM algorithm was 72%. Most of the mispredictions that occurred were for the specific behaviour 'breakfast', which occurred in the same location (kitchen) as lunch and snack. This is similar to the findings presented in Conference Article 2 [4], which used decision trees. It should also be noted that HMM is still a probabilistic algorithm, and consequently, its behaviour predictions are based on the highest probable path given an input sequence (cf. Journal Article 2 [2]). However, unlike decision trees, HMM was able to detect that the person was eating in the kitchen; it merely could not detect whether the person was having breakfast, lunch or a snack. Moreover, HMM was ultimately able to detect abnormal behaviour such as fall and change in the duration of behaviours when tested against the fictional dataset described in Section 5.3.

HSMM was also tested for use in HBM because it can explicitly model duration. However, it was found to be unsuitable because it required the individual to consistently follow exact behaviour patterns in order to model the duration. This constraint is impractical for HBM, since people do not always follow the same strict patterns within each activity and behaviour.

6.2 Part II: Health Care

This section summarises the Articles that examined some of the health care implications of HBM. Figure 7 shows the overview of the second part of this thesis.

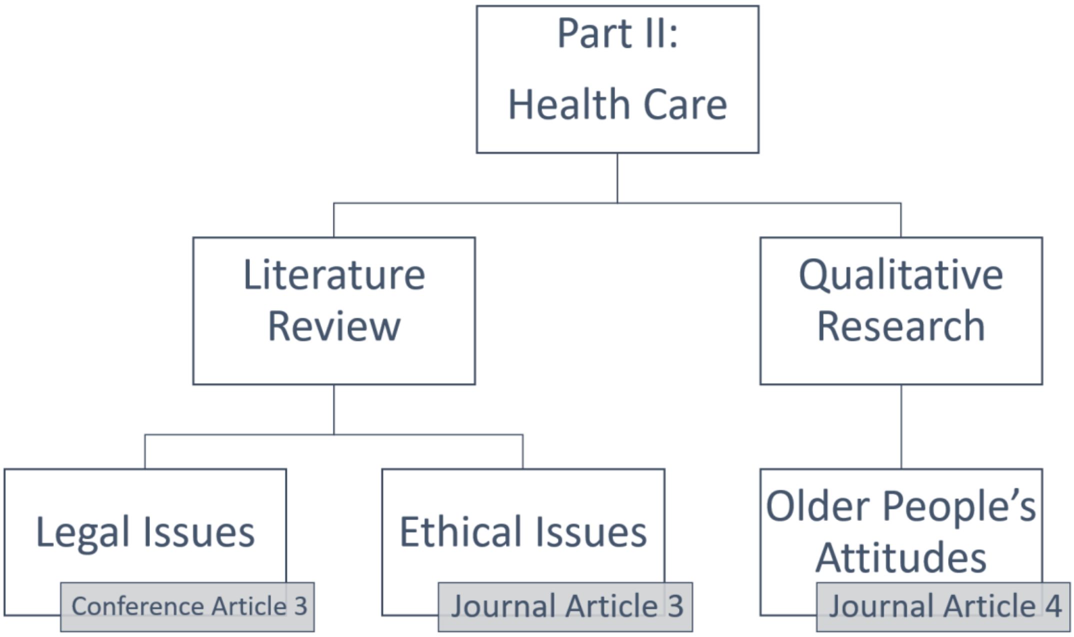

Figure 7. Overview of the health care–related Journal and Conference Articles.

6.2.1 Conference Article 3

Legal Aspects on Smart House Welfare Technology for Older People in Norway

Although legal issues are not directly related to health care, it is nonetheless important to investigate how the development of welfare technology might affect the legal rights of older people. Conference Article 3 [7] therefore consisted of a literature review focusing on the legal implications of implementing smart house welfare technology in Norway, where all of this thesis's research was conducted, in order to address legal barriers that might hinder the widespread adoption of welfare technology. Literature searches were therefore performed using both bibliographic scholastic (google scholar) and the law search (the Health Ministry regulations from Norway, the law from Norway and the European Union law). The results from both searches were clustered in groups to identify recurring topics: data privacy, data access and management, stakeholders' interests and informed consent of the users and/or their families. This research found that it is crucial to have proper legislation that handles data privacy and that the responsible for system failure should be a person capable of giving informed consent. Moreover, characteristics, limitations, and permissions in welfare technology should be stated clearly through a set of guidelines and standards.

6.2.2 Journal Article 3

Ethics of smart house welfare technology for older adults: a systematic literature review

After reviewing the potential legal implications of welfare technology, it was important to investigate its ethical implications. In Journal Article 3 [5], Hofmann's normative framework of 33 questions was used to identify ethical issues [106] and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were used for reporting [107]. A systematic review of the published literature identified 24 studies that were then synthesised by answering each of Hofmann's questions. The most important ethical issues related to the implementation of smart houses were determined to be cost effectiveness, privacy, autonomy, informed consent, dignity, safety, trust, legal aspects, and technology acceptance. Table 7 shows the number of publications that addressed each of the identified ethical challenges. As described in more detail in Journal Article 3 [5], it is important for designers of welfare technology to be mindful of these ethical challenges and limitations in order to build safe and dignified smart house conditions for older people.

Table 7. Number of publications related to the identified ethical issues. Table also reported in Journal Article 3 [5].

Ethical Challenges Identified	Number of Reports
Cost effectiveness	9
Privacy	8
Autonomy	7
Informed consent	6
Dignity	5
Safety	5
Trust	5
Legal aspects	4
Technology acceptance	4
Exclusion, depression and isolation	4
Reduction of human contact	4
Gap between designers and users	4
Technology testing/assessment	3

6.2.3 Journal Article 4

Older People's Attitudes And Perspectives Of Welfare Technology In Norway

This last Journal Article sought to explore older people' attitudes towards and perceptions of welfare technology. Conference Article 3 [7] and Journal Article 3 [5] indicated that it is important to consider end-users' feedback throughout the research and development stages in order to avoid their later rejection of the new technology. This is also consistent with the person-centred research principle of ensuring that an individual's values are central to decision-making [68]. Thus, in order to create a sustainable and targeted healthcare solution for older people, it is important to understand their opinions on welfare technology. Since there has been limited published research on this topic, semi-structured interviews were conducted with five women and four men above the age of 75. The collected data were then analysed using the qualitative content analysis method described by Graneheim and Lundman (cf. section 4 of this thesis) [98]. This analysis revealed two categories and four subcategories, as shown in Table 8.

Table 8. Results of the qualitative content analysis. Table also reported in Journal Article 4 [6].

Main theme	Categories	Subcategories
Welfare technology – a valuable addition to tomorrow's homes	I. Preferences and concerns about welfare technology	i. Feeling confident; a proactive approach to future technology
		ii. Concerns and dilemmas
	II. Reflections about today and tomorrow- awareness of personal health	i. Feeling healthy, independent, self-sufficient and safe
		ii. Facing own ageing- preparedness for unpredictable scenarios

The results showed that independence, autonomy and feeling safe were essential for the participants, but that they trusted the Norwegian health care system and did not depend on their families for care. Possibly for this reason, most participants also regarded welfare technology as enabling them to age in place and convenient. Furthermore, the participants already used technology in their daily lives and were confident with it. Surprisingly, they had no concerns about privacy, although some did mention concerns about loss of autonomy and dignity.

6.3 Integrating Parts I and II

6.3.1 Conference Article 4

Welfare Technology, Health Care and Behaviour Modelling – An Analysis

Throughout the research in the present thesis, gaps were found between the technical and health care aspects of welfare technology development, and these could lead to challenges when implementing welfare technology for older people. Most of the research related to welfare technology for older people refers to either its technical aspects or its health care uses, but few have deeply integrated both facets. Conference Article 4 [8]therefore sought to provide an overview of the relevant linkages and gaps. It identifies four important issues that should to be addressed when developing welfare technology: consistent terminology usage, use of a person-centred approach, ethical and legal considerations and older people' potential difficulties in interacting with welfare technology. Despite welfare technology's stated goal, its technical developers often neglect to consider older people' needs and desires [47], [108] (cf. also Journal Article 3 [5]). Collaboration between the health care and technical fields is a possible solution to ensure a person-centred approach. Health care researchers who work in the welfare technology field may also be better placed than technical researchers to help ensure that older people' needs are given priority over those of the researchers, industries, governments or any other involved parties.

7 Discussion

This section discusses and builds on the results that were described in the previous section. Consistent with the thesis structure, this section is divided into two parts that discuss the technical and health care aspects of HBM.

7.1 Part I: HBM

The main goal of this thesis was to explore the possibility of developing HBM for welfare technology. Previous studies have shown that welfare technology can help increase older people' abilities to age in place and that it is perceived as good care, in terms of both meeting older people' needs and being sufficiently easy to use [27], [109]. The welfare technology researched in this thesis attempts to model the behaviour of an individual who lives alone in a smart house environment and to be able to detect abnormal behaviour, in order to alert family members or caretakers if assistance is needed.

In order to create an HBM, a literature review was first conducted (Journal Article 1 [1]), which provided insights about several algorithms that could potentially be used to develop HBM. Machine learning algorithms were considered but discarded due to the amount of data needed for training. Instead, statistical methods were chosen because of their greater effectiveness with smaller datasets (cf. Section 3.4) [64]. Ultimately, three algorithms were chosen for further investigation: decision trees (Conference Article 2 [4]), HMM and HSMM (Journal Article 2 [2]).

The results of the decision trees algorithm were mostly successful. However, they did not enforce checks of all the parameters before estimating a decision, and when testing the decision tree model with the fictional dataset, the model failed to detect a possible fall. This suggests that while decision trees can be a good tool for HAR, with 88% accuracy, they are not the best method for HBM. Therefore, HMM and HSMM were next tested for use in HBM, and both provided superior results to the decision trees. However, HSMM proved to be impractical because it required that an individual follow the exact same pattern at all times. Although HMM, like the decision trees, also made erroneous predictions about activities performed in the same location, good results were obtained when the model was tested against the abnormal behaviours in the fictional dataset, and HMM was able to detect a possible fall as well as abnormal durational changes in some of the behaviours and to issue warnings accordingly. Although HMM's total behaviour recognition accuracy rate of 72% was lower than the 88% accuracy achieved using the decision trees algorithm, the decision trees model was not able to successfully detect abnormal behaviour. Therefore, in line with the goal of this thesis, HMM was determined to perform better than both decision trees and HSMM.

Developing HBM for an individual who lives alone is challenging, since the necessary data are usually obtained from sensors installed in a smart house. Due to limited resources, such data collection was not possible for this thesis. Instead, an open-source dataset was used in conjunction with a fictional dataset that was created as described in section 5 and in Conference Article 2 [4] and Journal Article 2 [2]. This allowed for the investigation of a general model that could be implemented for any individual. Such a model requires that data be collected for each individual before implementation of HBM, in order to allow the model to learn to identify an individual's normal behaviour patterns and detect abnormalities (cf. section 3.1).

7.2 Part II: Health Care Implications of HBM

As mentioned in Journal Article 3 [5] and Conference Article 3 [7] and 4 [8], it is important to address the health care implications of new technology for older people during the technology's research and development phases, and this was the focus of the second part of this thesis. A number of ethical and legal challenges may arise when developing and implementing welfare technology. These include cost effectiveness, privacy, autonomy, informed consent, dignity, safety, and trust (Table 7), as well as data access and management and stakeholders' interests. Some of these challenges may be difficult to fully overcome; nevertheless, they need to be considered when developing HBM for welfare technology.

Investigating the ethical challenges mentioned above are meant to provide information, bring awareness, and understanding in order to identify which of them are important considering when developing welfare technology. Solving the ethical challenges is beyond in the scope of this thesis. However, exploring user attitudes towards HBM could be a first step to find out which ethical challenges are major concerns for older people that could hinder the implementation of HBM for welfare technology.

Interviews were therefore conducted with nine older people to ensure some awareness of older people's experiences with and attitudes towards welfare technology in Norway. The interview results indicated that the participants were aware that ageing could be accompanied by frailty and vulnerability, especially when living alone, and they recognised the need to adapt as they aged and were open to making changes as needed. Many participants were therefore glad to learn about the development of HBM for welfare technology, which they regarded as increasing their safety while preserving their autonomy. Privacy was not an issue for most of the participants; instead, autonomy and safety were more important for them. It is worth noting that future generations of older people may think differently about privacy. Thus, more study in this topic should be done in the future.

Furthermore, as discussed in Journal Article 4 [6], all participants stated that they trusted the Norwegian healthcare system. Norway, along with other Scandinavian countries, operates a 'welfare state' that emphasises egalitarianism and individual autonomy regardless of social class [110], and Scandinavians, therefore, believe in freedom, autonomy and the right to good public services. This Scandinavian attitude may help explain why most participants expressed positive views about the use of HBM for welfare technology, which they perceived as allowing them to age in place for as long as they wished while also ensuring their safety.

Conference Article 3 [7] discussed the issue of informed consent. A new study suggested the implementation of a 'technological will' [111], with the idea being that the person could provide informed consent about under what circumstances technology could be used in his or her case in the future. The technological will would be drafted at the time of acquiring the new technology. This would allow the person's will to be fulfilled in case the person's cognitive functioning deteriorated in the future. However, the drawback of this technological will is that, as the participants of Journal Article 4 [6] stated, the future is uncertain. Thus, it would be difficult to predict what needs one would have in the future.

Additionally, as noted in Journal Article 3 [5], some developers may, consciously or not, design technology that solves their own needs more than those of their target populations. It is necessary to ensure that older people' needs and desires remain the focus and priority of welfare technology development, consistent with a person-centred research principles [68].

A recommendation could be that rather than finding how to solve the mentioned ethical challenges, we should focus instead on making welfare technology trustworthy. Trust is of considerable importance and could promote the wide adoption of welfare technology. Older people find themselves asking whether they should trust the technology or not. This lack of trust can hamper the implementation of HBM welfare technology. Several studies have suggested that trust is essential to help individuals overcome perceptions of risk and uncertainty when using and accepting new technology [112]–[114]. Therefore, by making the person feel that they can trust the technology, they could feel safe to use it, and uncertainties such as privacy concerns could be reduced.

8 Strengths and Limitations

A significant strength of this thesis is its combined analysis of both the technical and health care aspects of using HBM in welfare technology. These include the attitudes of the intended end-users and bringing awareness about the ethical and legal challenges that welfare technology may present. This research can therefore help provide an overview of this relatively new technology. Another strength of this research is that, although it focused on the Norwegian context, its findings could be broadly relevant in other contexts in which publicly funded healthcare for older people is regarded as a natural right and an extension of individual autonomy [110].

A good dataset is a necessary prerequisite for research on behaviour recognition, modelling and prediction. However, finding an appropriate dataset for this research was challenging, as also noted by Ferrari [52]; it is difficult to obtain large relevant datasets in smart house environments, not least due to the difficulty of finding willing participants and the ethical considerations involved in performing human research of this nature. This limitation was overcome in the present research by using an open-source dataset, as described in section 5.1. Although this dataset is small and does not contain information about abnormal behaviours, this was in some regards a strength, because it allowed the HBM to more fully learn only normal behaviours, making it easier to detect later any aberrations. However, this also led to the necessity of manually creating an additional fictional dataset, which presents some limitations. Notably, fictional datasets may lack representative data; as discussed in Journal Article 3 [5] and Conference Article 4 [8], the needs of older people may not always be known to researchers. Moreover, there is typically no way to validate a dataset that has been randomly created by a researcher.

Another limitation of the datasets used in this thesis is that they contained a combination of *activities* and *behaviours*. For example, the dataset contained the *behaviours* of ‘breakfast’, ‘lunch’, ‘dinner’ and ‘snack’ instead of the *activity* ‘eating’. Although the HBM, using HMM, was able to detect that a person was eating in the kitchen, it was unable detect whether the person was having breakfast, lunch or a snack. A better prediction could likely have been made if the dataset contained only behaviours.

A limitation observed in the reviews in terms of ethical and legal aspects (cf. Journal Article 3 [5] and Conference Article 3 [7]) included the lack of clarity of the methodological quality of the reviewed articles. This could be explained by the fact that technology articles do not always report the details of their research methodology. Another limitation was that several reviewed articles lacked emphasis on the possible solutions for ethical and legal challenges. Although bringing awareness and understanding on the ethical and legal challenges fell within the scope of this thesis, future research should focus on methods to solve or approach these ethical and legal challenges.

Finally, certain limitations were encountered when developing the qualitative research as mentioned in Journal Article 4 [6]. In short, including participants from different regions, paying more attention to gender perspectives, different ethnicities, or different socioeconomic status could have ensured more varied or diverse opinions. Other limitations were the difficulty of recruiting participants and participants' lack of experience with HBM welfare technology. Nevertheless, Journal Article 4 [6] contributes to the limited knowledge regarding attitudes towards welfare technology among older people.

9 Conclusion and Future Work

The research in this thesis focused on HBM, a type of welfare technology that would allow to detect abnormal behaviours at an individual level and alert family members or caretakers. This research is important because of recent increases in older populations and older people' reported desires to age in place in Norway, the rest of Scandinavia and in other developed countries. Welfare technology offers the promise of helping older people remain at home for as long as they wish in safe and dignified living conditions.

The thesis sought to discover whether a model could learn to recognise the behaviour patterns of an individual living alone sufficiently well to detect abnormal behaviours. This research was underpinned by the theory that all individuals develop unique behaviour patterns in their daily lives that could be recognised by an algorithm. The thesis therefore explored various HBM methods and ultimately concluded that an HMM could provide the best detection of abnormal behaviours, including falls. Decision trees and HSMMs were also tested, but their results were less promising.

The use of HBM in welfare technology is still in the early stages of development, and ethical and legal challenges still need to be addressed before its implementation. Most importantly, older people' attitudes towards it should also be more fully explored. In the present study's research among older people in Norway, participants regarded the use of HBM for welfare technology as empowering and as a means to age in place while preserving their safety, independence and autonomy. Further research is needed to see if these results can be replicated among larger and more diverse samples in a variety of national and cultural contexts'.

Future research should also consider the use of other algorithms to develop HBM, including machine learning techniques, which the present thesis was unable to investigate due to the challenge of finding sufficiently large datasets. Ideally, future research should start by collecting real data from a number of older adult volunteers. This would also likely require some research investment in a smart house or apartment with sensors, in order to collect the necessary data. Conversely, sensors could be installed in a volunteer's existing home; this would be ideal, since it would not require the participant to leave his or her home for an unfamiliar environment and might allow for data to be collected over a longer period of time. A single dataset that contained both normal and abnormal behaviour would also facilitate the task of teaching a model to recognise and predict an individual's normal behaviours, but no such dataset currently exists. The creation of such a dataset would greatly enhance future HBM research.

Additional work is also needed to interview slightly younger people (60–75 years old) than those targeted by the present research. This population might well have different concerns regarding the use of such technology, including greater concerns related to privacy, as compared to the older people (> 75 years old) interviewed in this thesis, but their views are important as they may still be among the first group with a widespread ability to implement welfare technology.

Finally, as mentioned in the Section 0, more research needs to be done on how to solve the legal and ethical challenges reviewed in Journal Article 3 [5] and Conference Article 3 [7]. The ethical and legal challenges could hinder the wide adoption of HBM for welfare technology. Thus, it is important to consider methods to solve the privacy, autonomy, dignity, trust, and informed consent challenges.

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Appendix

A Terms definition

In this Appendix, the terms used in the present dissertation are defined alphabetically.

Activity refers to the activities of daily living (ADL), the performance of the basic activities of self-care, such as dressing, ambulation, or eating (MeSH definition).

Ageing in place: helping older people to remain living at home.

Ambient assisted living (AAL): ''Assisted living technologies based on ambient intelligence are called ambient-assisted living (AAL) tools'' [23]. Known as welfare technology in Scandinavia.

Behaviour: the combination of activity, duration, location and posture of the person.

Duration: The time span from the start to the end of an activity, given in hours, minutes and seconds (hh:mm:ss).

Location: place where the person is doing the activity in the smart house (bedroom, bathroom, kitchen, etc.).

Posture: position of the person (lying, sitting, standing).

Smart house: any living environment carefully designed to assist residents in carrying out daily activities and to promote independent lifestyles [5], [27].

Welfare technology: ''technology used for environmental control, safety and wellbeing in particular for elderly and disabled people" [17].

B Norwegian to English terms

Following are the translation of Norwegian terms to English.

Helsetjenester i hjemmet (tidligere kalt hjemmesykepleie): home health care

Langtidsopphold i institusjon (sykehjem): long-term stay in institution (nursing home)

Praktisk bistand til daglige gjøremål (tidligere kalt hjemmehjelp): practical assistance for daily tasks

Articles

Journal Article 1

A review of smart house analysis methods for assisting older people living alone

Sánchez, Veralia, Carlos Pfeiffer, and Nils-Olav Skeie

Journal of Sensor and Actuator Networks 6.3 (2017): 11

DOI: 10.3390/jsan6030011

Journal of
Sensor and Actuator Networks

MDPI

Review

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

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Received: 18 May 2017; Accepted: 14 July 2017; Published: 21 July 2017

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

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.

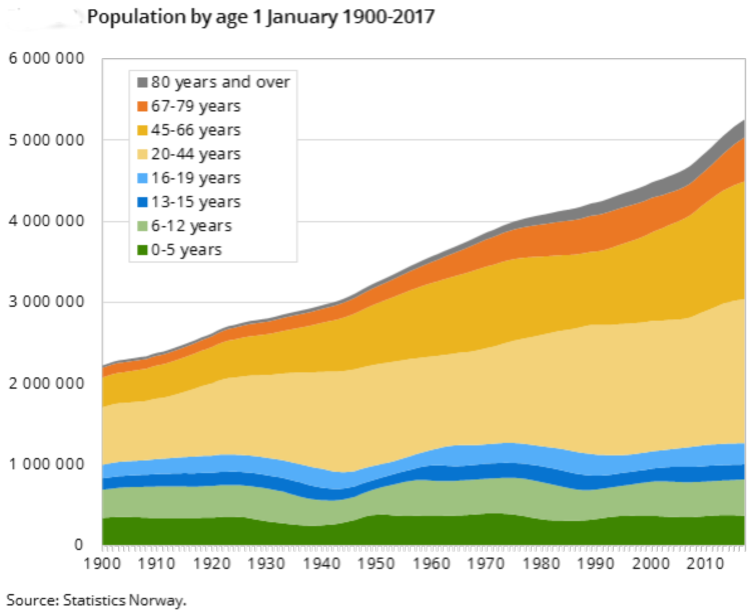

Figure 1. Statistics Norway [8].

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.

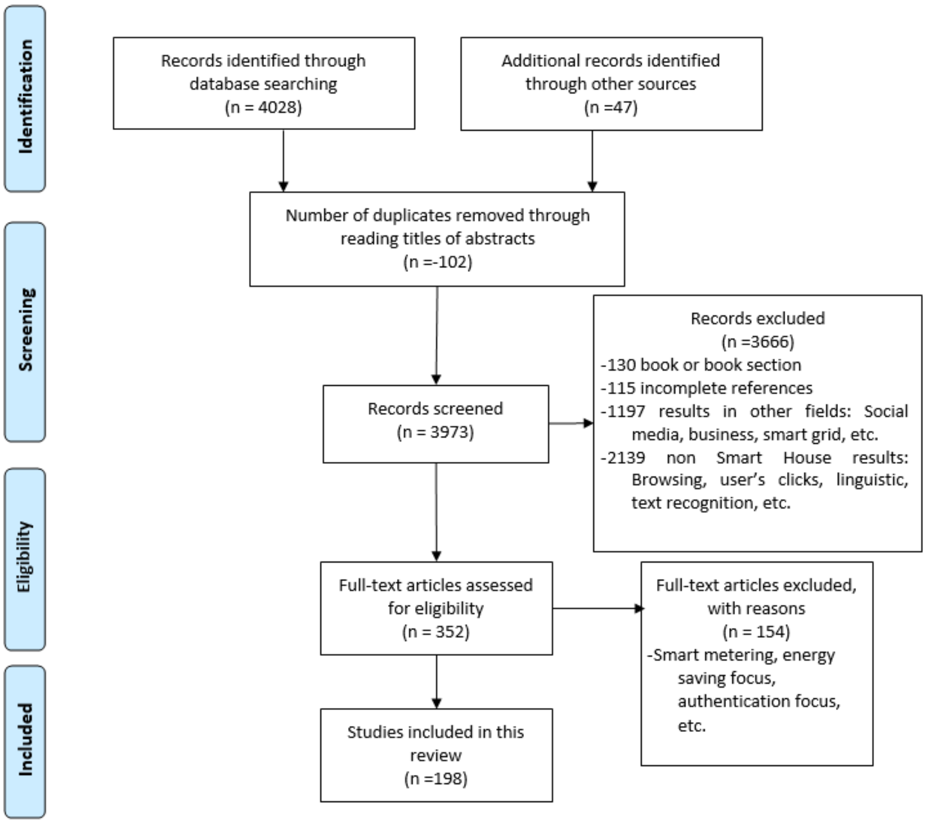

Figure 2. Database Search.

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.

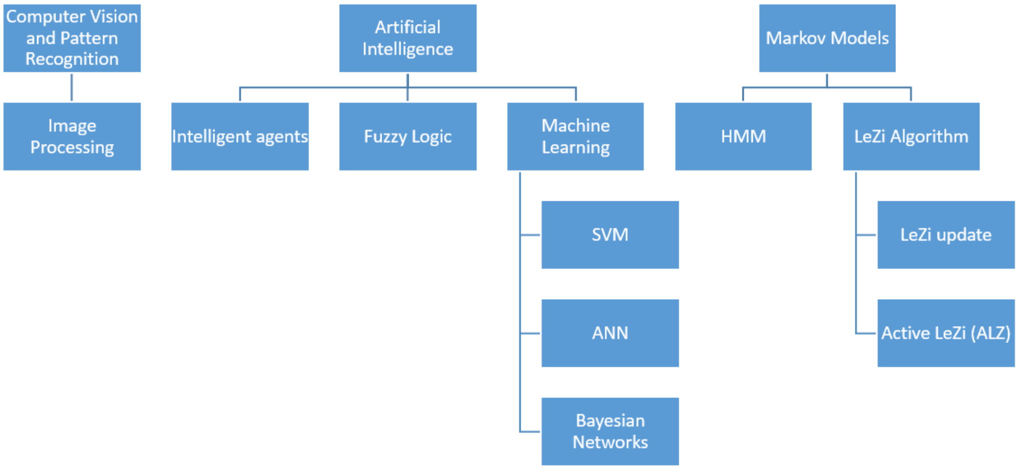

Figure 3. Analysis Methods.

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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Journal Article 2

Human behaviour modelling for welfare technology using Hidden Markov models

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Pattern Recognition Letters (2019)

DOI: 10.1016/j.patrec.2019.09.022

ARTICLE IN PRESS
JID: PATREC [m5G;October 7, 2019;16:45]

Pattern Recognition Letters xxx (xxxx) xxx

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Human behaviour modelling for welfare technology using hidden Markov models

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A R T I C L E I N F O

Article history:
Received 29 June 2018
Revised 10 September 2019
Accepted 23 September 2019
Available online xxx

Keywords:
Ambient assisted living
HMM
Behaviour recognition
Assistive technology
Pattern recognition
Norway
Smart house

A B S T R A C T

Human behaviour modelling for welfare technology is the task of recognizing a person's behaviour patterns in order to construct a safe environment for that person. It is useful in building environments for older adults or to help any person in his or her daily life. The aim of this study is to model the behaviour of a person living in a smart house environment in order to detect abnormal behaviour and assist the person if help is needed. Hidden Markov models, location of the person in the house, posture of the person, and time frame rules are implemented using a real-world, open-source dataset for training and testing. The proposed model presented in this study models the normal behaviour of a person and detects anomalies in the usual pattern. The model shows good results in the identification of abnormal behaviour when tested.

1. Introduction

The older population in Nordic and other European countries has substantially increased. In the European Union, 5.5% of the population is aged 80 or above as of 2017. This number will almost double to 12.7% by 2080 [1]. In Norway, 38.5% of households with people aged 65 and over live alone [2].

In Nordic countries, the term *welfare technology* refers to "technology used for environmental control, safety and well-being in particular for elderly and disabled people" [3]. Welfare technology is more often referred to as *ambient assisted living* outside of Scandinavia.

In this research, human behaviour modelling (HBM) is proposed as a type of welfare technology that can recognize an individual's behaviour patterns in a smart house, thereby helping to construct a safer environment. Smart house development is important for those who prefer to live in their own homes as long as they can care for themselves, also known as ageing in place, and are defined as living environments designed to assist residents with their daily activities and to promote independent lifestyles [4].

Therefore, HBM is developed to detect abnormal behaviour (anomalies) in a person's behaviour patterns and provide assistance if needed. "Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behaviour" [5]. Examples of abnormal behaviour could be falls and early signs of dementia.

In the present study, the term *behaviour* refers to the activity, duration of activity, location, and posture of a person. Recognizing a person's behaviour patterns helps in constructing a safer environment for older adults, people with disabilities, and a more comfortable lifestyle in general for any person.

The research presented here is based on the theory that people generate patterns in their daily activities and behaviour [6,7]. Therefore, a repetitive pattern in the person's behaviour helps to recognize, model, and predict future events.

In order to recognize the behaviour of a person, Hidden Markov models (HMM) were used. Posture checking and time frame logic were added as an extra layer of recognition to model the behaviour of the person as normal or abnormal.

HMM was used because it is a statistical method that assumes a Markov process with missing or unobserved states. Moreover, the Markov assumption is a sequence of events in which the probability of each event depends only on the previous event.

For the modelling, a real world, open-source dataset was used. The dataset comprised a finite number of days, in which half the

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https://doi.org/10.1016/j.patrec.2019.09.022
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days were used for training and the other half for testing. Once the HMM model was trained, the Viterbi algorithm was used to test the validity of the model for the remaining days in the dataset. The Viterbi algorithm enables detecting whether the input sequence for testing (or a new input sequence) is classified as a normal or an abnormal behaviour.

1.1. Aim and objectives

The aim of the present study is to model the behaviour of a person living in a smart house environment, to detect abnormal behaviour and alert family or a caretaker if assistance is needed.

The main objective of using HMM for human behaviour modelling is to predict whether the current activity is normal or abnormal. HMM is used because it is a statistical method that works well with a small dataset or insufficient training data [8,9].

1.2. Activity vs behaviour

In the present study, the term *activity* refers to the actions of people in a specific room or area. These actions are known as activities of daily living (ADL) and include sleeping, personal hygiene, showering, dressing, undressing, eating, etc. ADLs are more formally defined as the actions that require “basic skills and focus on activities to take care of one’s own body” [10].

The term *behaviour* in the present study refers to the combination of activity, duration, location and posture of the person.

- **Activity**: ADL.
- **Location**: place in the house where the person is doing the activity (bedroom, bathroom, kitchen, etc.).
- **Posture**: position of the person (lying, sitting, standing).
- **Duration**: The time span from the start to the end of an activity, given in hours, minutes and seconds (hh:mm:ss).

An example of a behaviour can be having breakfast. The breakfast behaviour comprises eating (activity), being in the kitchen (location), sitting (posture) and within a time span (duration). Behaviour can also be a sequence of activities.

The rest of this paper is organized as follows. In Section 2, presents the background. Section 3 discusses the methods. Section 4 describes the experiments. Section 5 presents the results and Section 6 discusses the results. Finally, the conclusion is provided in Section 7.

2. Background

Improving the lives and safety of older adults has been an important area of research with regard to smart house welfare technology [11–13]. This generally includes detecting falls, among other issues, and warning family or caretakers of any potential dangerous or abnormal situation [14–16].

Ideally, a smart house designed to help people should search for patterns in the user’s activity or behaviour and detect any deviation from this pattern. Other projects aim to ease a person’s daily life regardless of age, while increasing comfort and security [17].

The general technique used to achieve the aforementioned goals is Human Activity Recognition (HAR), which is the task of recognizing the activities of a person. There are several analysis methods used for HAR [18]. However, studies involving human behaviour modelling have not received the same kind of attention.

One study involving HAR modelling used decision trees with promising results of 88.02% for the activity recognition task. However, they study concluded that for modelling human activities, decision trees did not meet the expectations [19].

Therefore, in this section, we use the knowledge derived from the state-of-the-art techniques in HAR as a foundation for the present study in human behaviour modelling. Among the most popular analysis methods used for HAR are machine learning techniques and statistical methods.

Machine learning techniques require a large amount of data for training. In contrast, classic statistical methods are more effective than machine learning techniques when a smaller dataset is used [20]. Therefore, for pattern recognition within smart houses, a statistical approach tends to perform better since the datasets are usually small.

Useful statistical algorithms include HMM and Hidden Semi-Markov Models (HSMM). HMM have been used for several other tasks with excellent results, such as speech recognition, pattern recognition and artificial intelligence [21].

One of the first works on HMM for HAR is the work of Yamato et al. [22]. Later on, HMM has been used separately or in combination with other methods such as neural network and intelligent agents [23,24]. The centre for advanced studies in adaptive systems (CASAS), from Washington State University, implemented HMM with promising results with several residences in a smart house [25]. Another study on HAR for diabetes patients in a smart house was developed using HMM with 98% accuracy [26].

Several other studies are not traditionally called HAR but ADL recognition or detection. Both HAR and ADL recognition works have the same aim. A two-stage, multi-Markov model for ADL detection was used by Kalra et al. [27]. Another study used the dataset from CASAS to recognize ADL [28] and compared support vector machines (SVM), HMM, Fishe kernel learning (FKL) and random forests (RF). Gayathri et al. [29] also used the dataset from CASAS to detect ADL using Markov logic networks.

In addition, ADL recognition has been studied with HSMM. One of the first research on modelling ADL is the work of Duong et al. [11], who used a Switching Hidden Semi-Markov model (S-HSMM) for activity recognition and abnormal detection in a pervasive environment. Duong created a double-layered extension of HSMM. That model focused on distinguishing a person’s major routines (making breakfast, eating breakfast, etc.). Another very important work on HSMM for HAR used on real world activity recognition data is the work of Van Kasteren et al. [30].

The studies mentioned so far focus on HAR/ADL recognition using HMM. There are, however, other studies that use other techniques for HAR recognition, such as machine learning techniques.

One machine learning technique for anomaly detection is Hierarchical Temporal Memory (HTM). Some studies have used HTM for anomaly detection in streaming data, online sequence learning and short-term forecasting of electrical load time series [31–33]. However, there are very few works using HTM for abnormal behaviour detection for welfare technology.

Although machine learning techniques could be useful for HBM, they require large amounts of data [20]. This is particularly a problem in smart house environments, where it is difficult to obtain large relevant datasets. Finding a person who is willing to live in a smart house that is set up to collect data is challenging, especially if the final user in an older person, where many ethical challenges are involved [4]. Therefore, the data used in this study is an open-source small dataset.

In addition, anomalies in the behaviour of a person cannot as of yet be learned from the currently available dataset. The publicly available datasets comprise a person living alone for a few days or months and performing his or her daily activities. The datasets do not contain any abnormal behaviour in their patterns. Therefore, in the present study, we have created a fictional dataset with abnormal behaviour to test our model.

The studies described in this section show that HMM has been implemented with good results for HAR/ADL. Therefore, in the present study, HMM is implemented for the first step of human behaviour modelling.

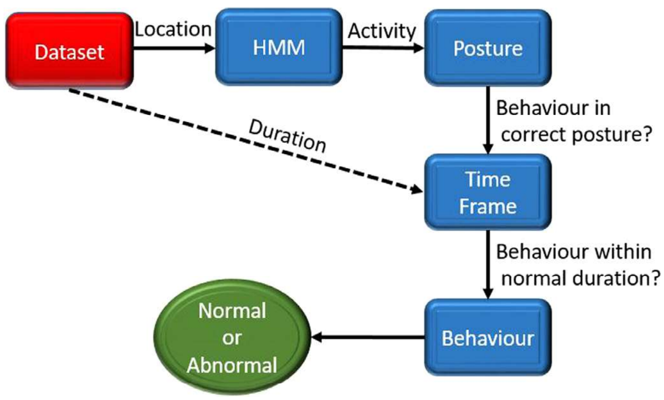

Fig. 1. Flow diagram of proposed methodology for HBM.

Table 1
Attributes of the *OrdonezA* dataset used [37].

Name	Value
Setting	Apartment
Number of locations	4 Rooms and hall/entrance
Number of labelled days	14 days
Labels (ADLs included)	Leaving, Toileting (Personal hygiene), Showering, Sleeping, Breakfast, Lunch, Dinner, Snack, Spare Time/TV, Grooming
Number of sensors	12 sensors
Sensors	PIR: Shower, Basin, Cooktop Magnetic: Maindoor, Fridge, Cabinet, Cupboard Flush: Toilet Pressure: Seat, Bed Electric: Microwave, Toaster

3. Methods

3.1. Design

First, the HMM algorithm was implemented. The activities of the person can be modelled as Markov chains. Therefore, HMM was implemented in order to train the algorithm and recognize the activities. The person's activities were used as the hidden states, and the observable states were the person's location (obtained from the sensor data in the dataset). MATLAB was used to implement the HMM.

The HMM was trained using the Baum–Welch algorithm. Later, the Viterbi algorithm was used to find the most probable activity given the input sequence.

The HMM module outputted the activity of the person. The person's posture was then checked using a Boolean method to detect abnormal behaviour such as falls (Section 4.2). Afterwards, time rules were applied, considering the duration for each activity. The time frame rules enable more accurate detection of any abnormal behaviour in the person (Section 4.3). Fig. 1 shows the proposed methodology used in the present research.

HSMM was also used in the present study as an alternative to HMM. HSMM was chosen because HSMM "can have any arbitrary duration distribution" [34]. The HSMM implementation was programmed with the *mhsmm* package for R [35]. The main reason for using HSMM was to compare the performance of HMM and HSMM with regard to HBM.

Table 2
Example of *Day 1* in the dataset. The dataset comprises the date, start time, end time, activity and location. To train the HMM, *location* was used as an observable variable and *activity* was used as the hidden variable.

Date	Start time	End time	Activity	Location
28-11-11	02:27:59	10:18:11	Sleeping	Bedroom
28-11-11	10:21:24	10:23:36	Toileting	Bathroom
28-11-11	10:25:44	10:33:00	Showering	Bathroom
28-11-11	10:34:23	10:43:00	Breakfast	Kitchen
28-11-11	10:49:48	10:51:13	Grooming	Bathroom
28-11-11	10:51:41	13:05:07	Spare_time/TV	Living room
28-11-11	13:06:04	13:06:31	Toileting	Bathroom
28-11-11	13:09:31	13:29:09	Leaving	Hall
28-11-11	13:38:40	14:21:40	Spare_time/TV	Living room
28-11-11	14:22:38	14:27:07	Toileting	Bathroom
28-11-11	14:27:11	15:04:00	Lunch	Kitchen
28-11-11	15:04:59	15:06:29	Grooming	Bathroom
28-11-11	15:07:01	20:20:00	Spare_time/TV	Living room
28-11-11	20:20:55	20:20:59	Snack	Kitchen
28-11-11	20:21:15	02:06:00	Spare_time/TV	Living room

Table 3
Assigned number and posture of the person according to the activities.

Number	Posture	Allowed activity
1	Lying	Sleeping, Spare time
2	Sitting	Personal Hygiene, Breakfast, Spare time, Snack, Lunch, Dinner
3	Standing	Showering, Grooming, Leaving

3.2. Data

The data used for this study come from an open dataset named *Activities of Daily Living (ADLs) Recognition Using Binary Sensors Data Set*, available for download [36]. The data collected comprise information about the ADLs gathered by two people living on a daily basis in their own homes. The dataset is in a text file format.

The dataset properties are depicted in Table 1. The information in the dataset includes the date, time, location of the sensor, type of sensor, location (room) in the apartment and activities.

Note that in the present research, we used the same terms as they are used in the dataset. Therefore, the term *toileting* is used as it is instead of the more proper term *personal hygiene*.

There are two instances of data, one of 14 days (OrdonezA), and one of 21 days (OrdonezB), corresponding to each user, person A and person B, respectively. The activities were manually labelled by the users. Both dataset *OrdonezA* and dataset *OrdonezB* were used in this study.

An open-source dataset was chosen in order to obtain unbiased results. In addition, this dataset comprises real-world data and it has been used in other research [37]. The fourteen days' activity data for the first dataset is shown in Fig. 2.

3.2.1. Data handling

The dataset is a text file that can be imported into MATLAB. Each day in the dataset represents a day sequence.

For *OrdonezA*, seven days were used as a training sequence, and another seven days were used as a testing sequence. For *OrdonezB*, fourteen days were used as a training sequence, and another seven days were used as a testing sequence.

The house room *location* was chosen as the main observed variable, and the *activities* were the hidden data. Table 2 depicts the first day from the dataset.

An additional column for *posture* was added to the dataset. The values of the *posture* variable were *lying*, *sitting* and *standing*. The values were assigned according to each activity and coded to numbers in order to develop the MATLAB code. Table 3 shows the values allowed for each activity.

A total of 10 *activities*, 5 *locations* and 3 *postures* were used.

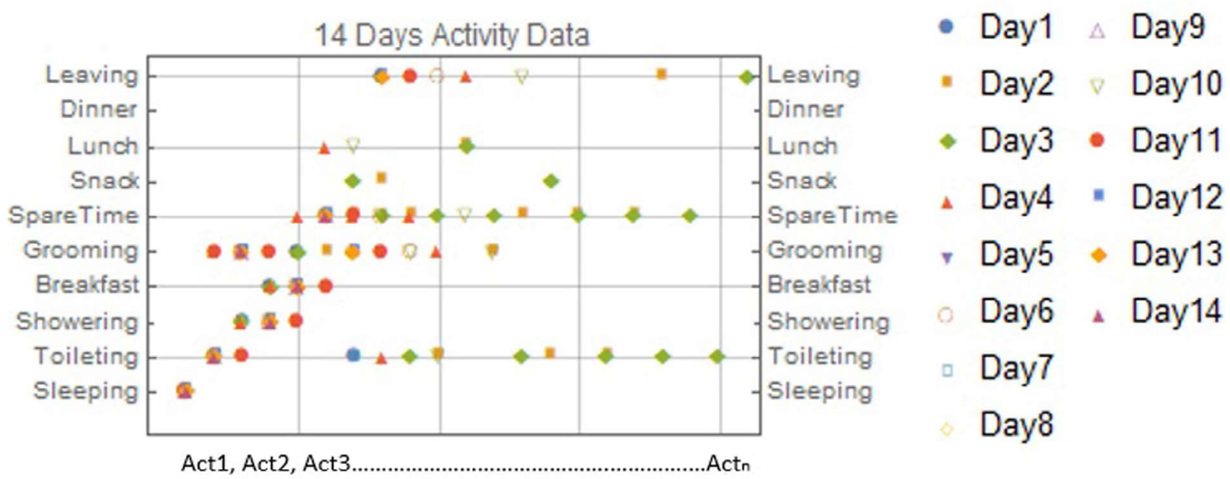

Fig. 2. Activity data graph. Each day is shown in a different colour, according to the legend at the right. The first activity is always *sleeping* and the last activity is *leaving*. The activities are shown in a sequence.

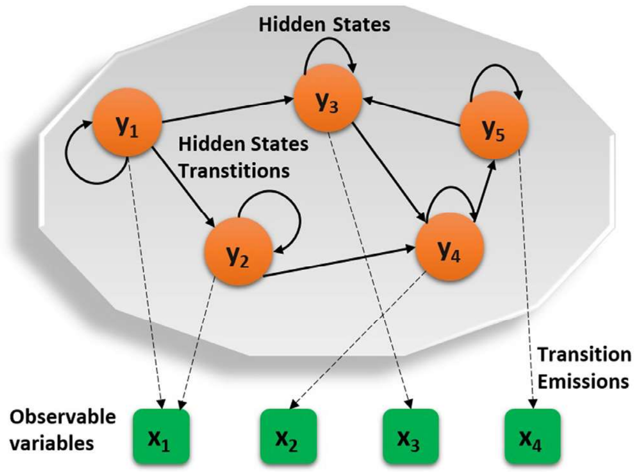

Fig. 3. Schematics of HMM representation.

3.3. Hidden Markov model

The idea of Hidden Markov Models (HMM) was first introduced in the late 1960s [9]. HMMs are a "subclass of Bayesian networks known as dynamic Bayesian networks" [21]. HMM is a generative probabilistic model that is used for generating hidden states from observable data.

HMMs utilize Bayesian rules such that a separate model $p(x|y)$ is learned for each class. Therefore, the posterior probability $p(y|x)$ can be calculated.

Fig. 3 shows a schematic of HMM. The *Xs* are the observable variables and the *Ys* are the hidden variables. The observed variable (sometimes called the *event*) occurs at each instant of time. The hidden variables, *Ys*, can be observed by another set of stochastic processes that produce the sequence of observations *Xs* [9]. Each hidden state y can emit one and only one possible observed variable x.

The HMM is fully determined by three probabilities:

1 The transition probability (A)
  - $p(y_{t+1}|y_t)$
2 The emission probability (B)
  - $p(x_t|y_t)$
3 The initial state distribution (π)
  - $\pi(y_0)$

The aim of the HMM is to solve the following three problems:

1 **Evaluation**: Inferring the probability of an observation sequence given the fully characterized model.
2 **Decoding**: Finding the path of hidden states that most probably generated the observed output.
3 **Learning**: Optimizing the model that best describes how a given sequence of observations (also known as a *training sequence*) occurs.

In the present study, the focus is on learning and decoding to recognize the behaviour of the person.

3.3.1. Hidden semi-Markov model

HMM does not take into account the duration parameter of the current activity. Therefore, to model the behaviour of the person, an additional layer is needed to consider the duration.

To overcome this additional layer, HSMM were also studied as an alternative solution for behaviour modelling.

HSMM is an extension of HMM. HSMM allows "the underlying process to be a semi-Markov chain with a variable duration or sojourn time for each state" [38].

The HSMM can produce a sequence of observations. The number of observations that are emitted during state i is constrained by the length of time spent (duration) in state i, usually represented as d. Thus, for each state i, there is a specified duration distribution D_i, which can be parametric or non-parametric.

As a result, the HSMM parameters are the same as the HMM, plus the sojourn time for each state. $\lambda = (A,B,D,\pi)$.

Fig. 4 shows a representation of the HSMM. The HSMM runs from 1 to T times, where x is the current observation, y is the current state and d is the duration variable of the current state. Thus at each step, the variable comprises $V_t = \{y_t,d,x_t\}$. Each state duration can be modelled by any distribution in the exponential family.

4. Experiments

The experiments were performed for both available datasets, *OrdonezA* and *OrdonezB*. However, in this section, the figures and explanations are only provided for the first dataset *OdonezA* in order to keep the text as clear as possible. Section 5 provides the results for both datasets. The experiments with the *OrdonezB* dataset

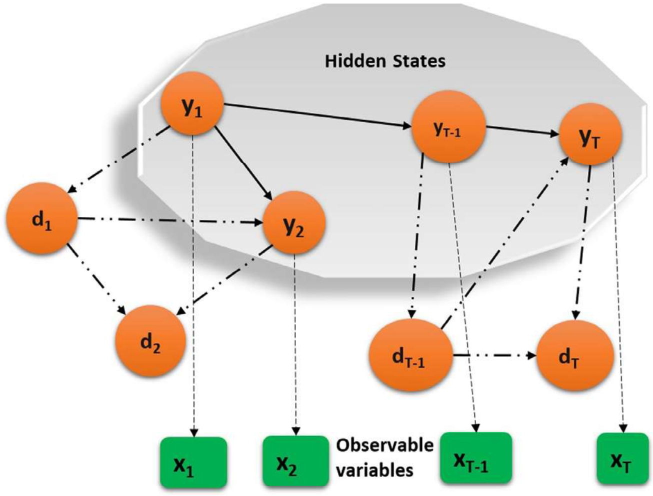

Fig. 4. Schematics of HSMM representation.

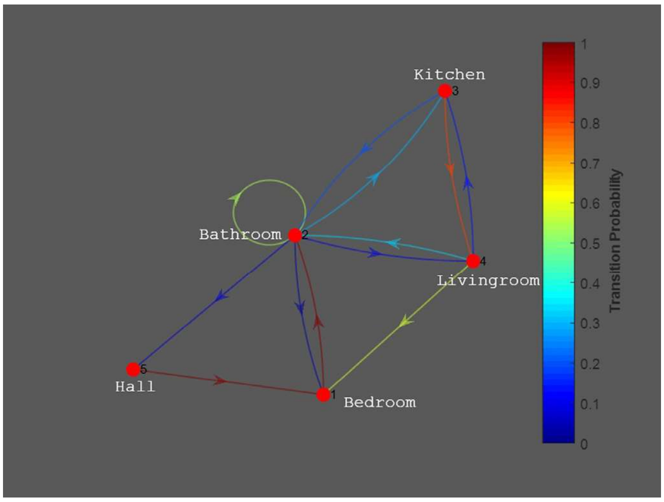

Fig. 5. Location transition with heat transition scale probability on the right side. The transitions were estimated using the Baum–Welch algorithm.

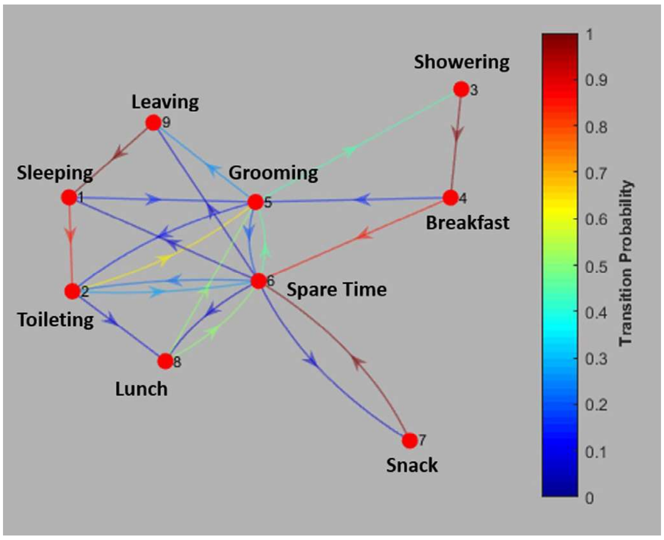

Fig. 6. Activity transition probabilities after the HMM was trained using the Baum–Welch algorithm.

follow the same procedure as described here for the *OrdonezA* dataset.

4.1. HMM and HSMM

The HMM was built by initializing the transition and emission probabilities (A and B). The *activities* data corresponded to the hidden state, and the *location* data corresponded to the observed data (traning sequence). The HSMM was built with the sojourn time *D*.

4.1.1. The learning task

The learning process deals with how to adjust the model parameters $\lambda = (A,B,\pi)$ to maximize the probability of the observation sequence $p(X|\lambda)$, where *X* represents the observed sequence, $X = x_1, x_2, x_3, \ldots x_n$. The idea is to optimize the model parameters that best describe how a given observation sequence is produced [9]. The Baum–Welch algorithm is used for this.

For the *OrdonezA* dataset, the first seven days were used to train the model; this is known as the training data. The last seven days were used for testing. For the *OrdonezB* dataset, the first fourteen days were used to train the model and the last seven days were used for testing.

The training sequence uses the *location* data as the observable sequence. The dataset comprises five room locations, as depicted in Table 1.

Fig. 5 shows the transition between the *locations*, estimated with the Baum–Welch algorithm. That is, *A(i,j)*, the probability of transition from state *i* to state *j*, given the training input sequence of *location*.

The hidden variables were the *activities*. A total of ten activities were trained. However, there was no data for the *activity dinner* in the training dataset *OrdonezA*. Fig. 6 shows the trained HMM corresponding to the transition between the *activities*. In addition, a probability transition heat map of the *activities* is given in supplementary material (Fig. A.1).

4.1.2. The decoding: Viterbi algorithm

Once the model was trained and given a new observation sequence, it was possible to determine the best, most likely sequence of hidden states that produced that observable sequence. The Viterbi algorithm was used to achieve this decoding task.

The observation sequence was the *location* data of a day. A total of seven days was used for testing, comprising the last seven days of each dataset.

The prediction accuracy was found by computing the percentage of the real or actual sequence state that agreed with the predicted sequence. Hence, the formula:

$$\text{Accuracy} = \frac{\sum \text{actual state}}{\sum \text{predicted state}} = \text{total state}$$

4.1.3. HSMM

The HSMM was trained using the *mhsmm* package for R. The same parameters and training data as in the HMM were used. Only the duration parameter *D* was added to model the HSMM.

For the parameter *D*, the Gamma distribution was first used to model the duration of each activity. Second, a Poisson distribution was also used to model the duration of each activity.

4.2. Checking posture to detect possible fall

The *posture* of the person was checked using a Boolean logic method. The *posture* variable can have only three values: *lying, sitting* and *standing*. The primary check was applied to the posture *lying* because it could indicate a fall.

A priori knowledge was applied for this step. Therefore, the *lying posture* was only allowed in the *sleeping* and *spare time* activities, as shown in table Table 3. There should not have been any *lying* in any activity performed in the *locations: bathroom, kitchen* and *entrance*. If the posture *lying* was found in any of the aforementioned locations, then a fall was detected.

4.3. Time frame rules

Time frame rules were used to determine whether the current *activity* had a reasonable *duration*. The seven days that were used for training the HMM were also used for training the *duration* of each activity.

First, the *duration* of each *activity* was extracted from the dataset. Then, the minimum and maximum *duration* for each activity in the training dataset was computed. Finally, to calculate the *duration* range for each *activity*, a $\pm 20\%$ threshold was used. Therefore, 20% was added to the maximum *duration* of each *activity*, and 20% was deducted from the minimum *duration* of each *activity*.

- Maximum duration allowed = Maximum duration + 20%
- Minimum duration allowed = Minimum duration − 20%

If the person spent more than the maximum or less than the minimum duration allowed for any *activity*, an abnormal behaviour alert was triggered.

4.4. Fictional dataset test

The dataset used in the present study did not contain information about abnormal behaviour in its patterns. As mentioned in Section 2, we were unable to find a relevant dataset containing both normal and abnormal behaviour for a person living in a smart house. Therefore, it was not possible to learn abnormal behaviour from the dataset used in the present project.

To overcome this challenge, we manually created a small fictional dataset containing some abnormal behaviour comprising of three days. The data in the dataset contained some changes in the duration, posture, and sequence of activities. These three fictional days were created to test whether the model presented in this research could detect abnormal behaviour in the person's behaviour.

Therefore, the *duration* of some of the *activities* was exaggerated. In addition, on the first fictional day, the *posture* for the activity *leaving* at the *Entrance* was changed to *lying*, to simulate a fall. Finally, the sequence of *activities* on the third day was changed.

5. Results

5.1. Results on first dataset OrdonezA

As described in Section 4.1.2, the Viterbi algorithm estimates the *behaviour* of the person based on the observation sequence of the observable variable *location*. The last seven days were used for testing. The predicted *behaviours* were compared to the actual *behaviours* sequence in the dataset. The results for the *OrdonezA* dataset Day 8 and Day 10 are shown in Fig. 7. The supplementary material contains the results for all the test days in *OrdonezA* dataset (Fig. A.2).

For the first day in the testing dataset, it is possible to see that the predicted *behaviour* is *grooming* instead of *toileting*. The same is true for most of the other days. One possible reason for this estimation is that both of these *behaviours* are in the *bathroom location*.

In addition, the *behaviour breakfast* was predicted instead of the correct *lunch* and *snacking behaviours*. The same reason as before could be applied here, that the *behaviours breakfast, lunch* and *snacking* are all located in the *kitchen*. Therefore, the prediction accuracy was 72% using the HMM algorithm.

Table 4
Warnings in behaviours when *duration* is checked for the OrdonezA dataset. The first column is the day in the testing data. The second column shows the predicted behaviour. The third column shows the duration of the predicted behaviour.

Day	Behaviour	Duration	MinTime	MaxTime
Day 8	Grooming	00:00:05	00:00:09	00:11:16
Day 8	Sleeping	00:00:04	10:13:45	10:09:18
Day 8	Leaving	00:16:59	00:18:28	03:30:26
Day 8	Breakfast	00:43:08	00:03:40	00:12:44
Day 9	Grooming	00:13:38	00:00:09	00:11:16
Day 9	Breakfast	00:35:05	00:03:40	00:12:44
Day 10	Grooming	00:13:41	00:00:09	00:11:16
Day 10	Breakfast	00:35:56	00:03:40	00:12:44
Day 11	Leaving	03:49:40	00:18:28	03:30:26
Day 11	Grooming	00:00:02	00:00:09	00:11:16
Day 13	Leaving	04:03:00	00:18:28	03:30:26
Day 14	Grooming	00:15:46	00:00:09	00:11:16
Day 14	Breakfast	00:52:05	00:03:40	00:12:44

After the HMM results were obtained, the *posture* of the person was checked. There were no warnings when the *posture* was checked on any of the days assigned for testing because there was no abnormal behaviour in the testing dataset.

Finally, time rule was applied to the model to check the *duration*. Table 4 shows the warnings in the *behaviour* when the *duration* was checked. The results show that the model can detect whether the user has spent either too much or too little time performing a *behaviour*.

Most of the warnings are for the *behaviour breakfast*, because the *duration* of that *behaviour* varied a great deal. One reason for this is that the *behaviour breakfast* was predicted instead of the real *behaviour snack* or *lunch*, which usually take less time (*snack*) or more time (*lunch*).

Other warnings resulted for the *behaviour grooming* and *leaving*. Hence, the model detected that the person spent less time or more time than usual engaging in these *behaviours* and issued warnings.

The results for the fictional dataset are shown in Fig. 8. The results for the three fictional days show the *behaviour grooming* predicted instead of the *behaviour toileting* or *showering*. In addition, the second fictional day shows the prediction of the *behaviour breakfast* instead of *lunch*.

Regarding the check on the *posture* of the person, a warning was issued for the first fictional day: *"Warning: Person lying in Entrance, possible fall detected"*. Therefore, the model successfully checked the *posture* of the person and abnormal behaviour such as a fall was detected.

The model also issued another warning for the second fictional day as follows: "*Warning: Person is not lying while in bed*". Thus, the model detected the abnormal behaviour in the *behaviour sleeping*.

Other warnings were issued by the model regarding the duration of some of the *behaviour*. The model detected that the person spent less time than usual engaging in the *behaviour leaving* for the second and third fictional days. Therefore, a warning was generated, stating that "*The person came back too early*".

5.2. Results on the second dataset OrdonezB

The result graphs for the *OrdonezB* dataset are in the supplementary material (Fig. A.3). In short, fourteen days were used for training and seven days were used for testing.

The model predicted the *behaviour grooming* for several of the days in the testing dataset, instead of the real *behaviour toileting* or *showering*. As with the *OrdonezA* dataset results, this prediction

Please cite this article as: V.G. Sánchez, O.M. Lysaker and N.-O. Skeie, Human behaviour modelling for welfare technology using hidden Markov models, Pattern Recognition Letters, https://doi.org/10.1016/j.patrec.2019.09.022

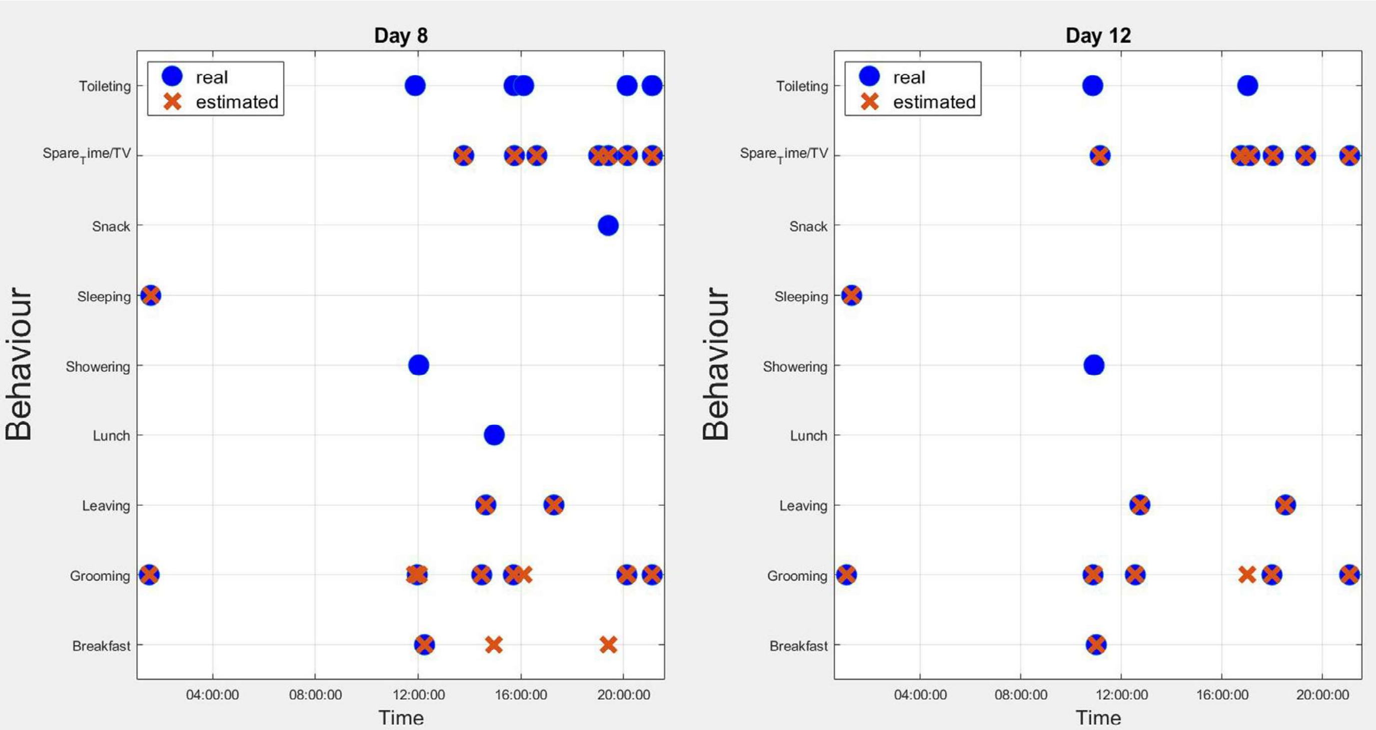

Fig. 7. Results for the OrdonezA dataset for day 8 and day 12: Blue circles show the real data. Red crosses show the estimated results.

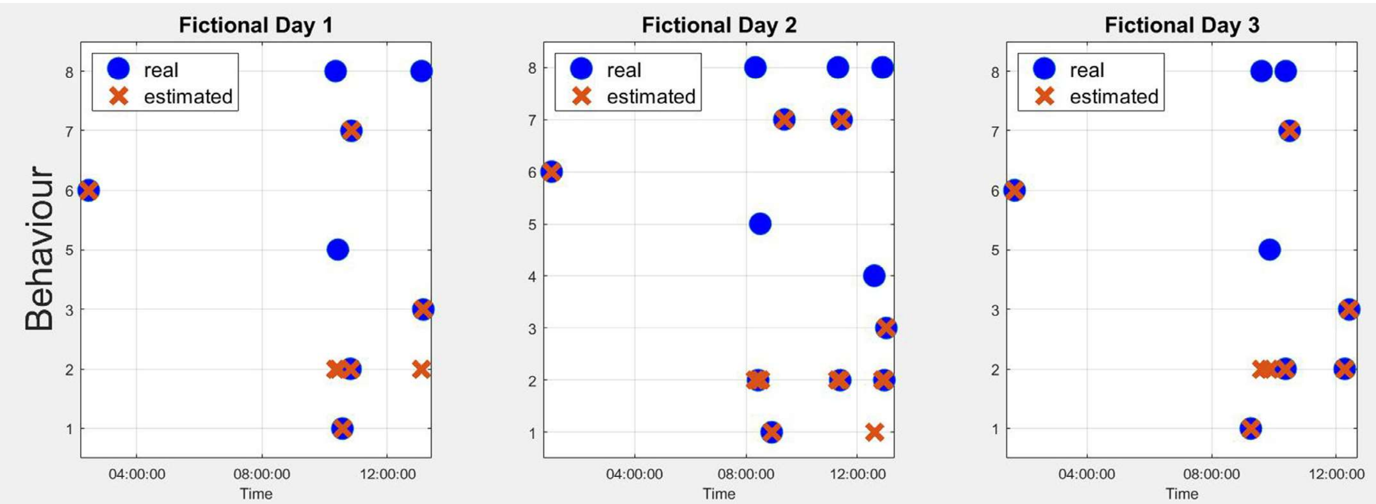

Fig. 8. Results for the three days in the fictional dataset. Legend in *x*axis is as follow: (1) Breakfast, (2) Grooming, (3) Leaving, (4) Lunch, (5) Showering, (6) Sleeping, (7) Spare time/TV, (8) Toileting.

was made because all three *behaviours* are performed in the *bathroom location*.

Similarly, the model predicted the behaviour *breakfast* instead of *lunch* or *snack* for several days in the testing dataset. The same reason as before applies here too: the *behaviours breakfast, lunch* and *snack* are all performed in the same *kitchen location*.

6. Discussion

In this study, a Hidden Markov model is used for predicting the behaviour of a person. The accuracy of the HMM is 72%. The results for both dataset *OrdonezA* and *OrdonezB* showed consistency in the predictions. Most of the mispredictions that occurred were for the *behaviour breakfast*, primarily because the *behaviours breakfast, lunch* and *snack* all take place in the *location kitchen*.

To overcome this challenge in the prediction, the ideal dataset should state the *activity eating* instead of the *behaviour breakfast*. However, a limitation was that the dataset used in the present study is a combination of *activity* and *behaviour*. Therefore, *breakfast* is a *behaviour* that includes the *activity eating*. The difference between *behaviour* and *activity* is defined in Section 1.2. This means that the model presented in the current study was able to detect that the person was *eating in the kitchen*, but it could not detect whether the person was having *breakfast, lunch* or *snacking*.

In addition, there should be enough training data to model a person's normal and abnormal behaviours. It is worth noting that the method used in the study is a probabilistic model. As a result, the *behaviour* predictions are based on the highest probable path given an input sequence. Hence, HMM has been shown to be a good method for HBM.

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HSMM was also studied for modelling the behaviour because the duration is modelled explicitly. However, for the aim of this study, HSMM does not meet expectations. The main reason for the poor results obtained with the HSMM is that a person's *behaviour* must follow the exact same pattern all the time in order to model the duration.

Previous research in HSMM for activity recognition has effectively distinguished between having *breakfast, lunch* or *dinner* [34]. However, those experiments were constrained to the person following the same pattern of opening the fridge and then using the stove, sink, cupboard and table in the same sequence. Only the duration changed for the sequence.

For modelling human behaviour in the present study, the constraint of following the same exact sequence is impractical, since people do not always follow the same strict pattern within each *behaviour*. Therefore, it was not possible to train the HSMM effectively as the dataset does not contain the same strict pattern for every day. Consequently, HMM was chosen as the best method for modelling a person's behaviour.

When the *posture* of the person was checked, the results showed that the model was able to detect a fall in the *entrance* in the dataset that was fictionally created. Hence, Boolean logic is a fast and effective method for the purpose of fall detection.

Lastly, the duration for each *behaviour* was checked using time frame rules. The current *duration* of each *behaviour* was extracted from the dataset. $A \pm 20\%$ approach was implemented to determine whether the current *behaviour* was within the normal *duration*. The results showed that the model could effectively detect whether the person has spent too much or too little time in an *activity*.

The *posture* was checked before the *duration* because in our estimation, detecting a fall is more important than the duration of a *behaviour*.

Finally, the model in the present study is tested offline. However, in the future, the model should be run in real-time. This means there should be a period of learning. The results presented in this study show that our model was able to learn from seven days. In addition, the real-time model should be able to check the *behaviour* of the person at fixed time intervals in order to detect whether the *behaviour* is normal or abnormal, such as using a time event driven logic every sixty seconds.

7. Conclusions and future work

Human behaviour modelling (HBM) for welfare technology is proposed to detect abnormal behaviour. HBM allows detecting any deviation from the usual or normal pattern of the person. Hence, abnormal behaviours are possible to detect and alert a family member or caretaker if the person is in need of any assistance.

The behaviour of the person consists of the activity performed by the person, the duration, the location and posture of the person. Hidden Markov models (HMM), is used to model and predict the behaviour of the person. The experimental evaluation shows good results using an open source real world dataset.

Future work should focus on studying other algorithms, including statistical, machine learning and deep learning with the aim of developing HBM with possible improvements and compare them with the performance of the present study.

Declaration of Competing Interest

None.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.patrec.2019.09.022.

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Human behaviour modelling for welfare technology using hidden Markov models- Supplementary Material

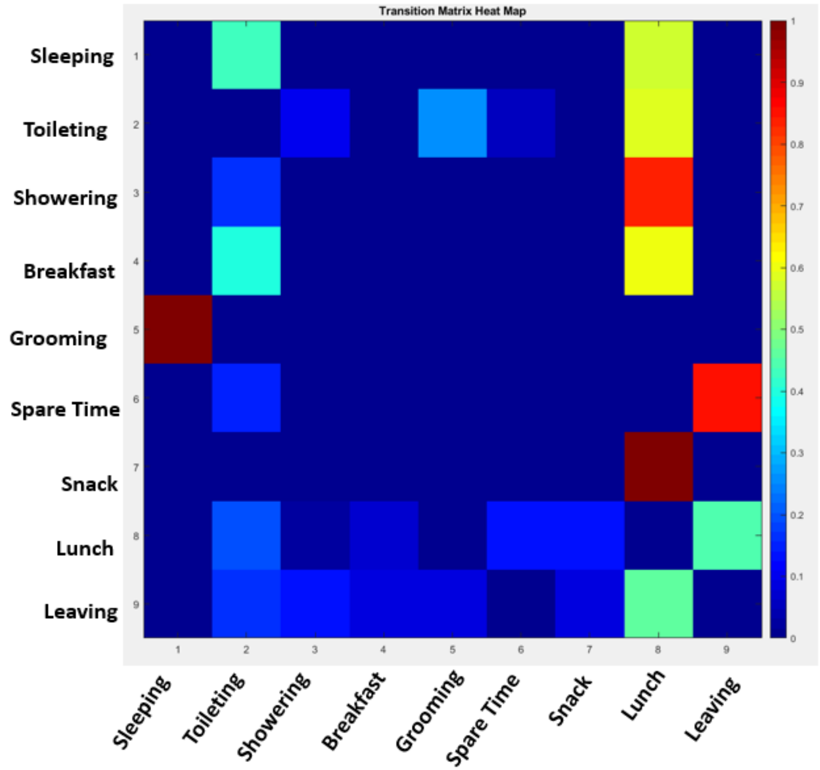

Fig. A.1: Activities transition heat matrix

Fig. A.2: Results for the OrdonezA dataset. Blue circles show the real data. Red crosses show the estimated results

Fig. A.3: Results for OrdonezB dataset: Blue circles show the real data. Red crosses show the estimated results

Journal Article 3

Ethics of smart house welfare technology for older adults: a systematic literature review

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International Journal of technology assessment in health care 33.6 (2017): 691-699

DOI: 10.1017/S0266462317000964

International Journal of Technology Assessment in Health Care, 0:0 (2017), Page 1 of 9.

doi:10.1017/S0266462317000964

Assessment

ETHICS OF SMART HOUSE WELFARE TECHNOLOGY FOR OLDER ADULTS: A SYSTEMATIC LITERATURE REVIEW

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Background: The University College of Southeast Norway has an on-going project to develop a smart house welfare system to allow older adults and people with disabilities to remain in their homes for as long as they wish in safe, dignified, living conditions.
Objectives: This article reviews reported ethical challenges to implementing smart houses for older adults.
Methods: A systematic literature review identified twenty-four articles in English, French, Spanish, and Norwegian, which were analyzed and synthesized using Hofmann's question list to investigate the reported ethical challenges.
Results: Smart houses offer a promising way to improve access to home care for older adults and people with disabilities. However, important ethical challenges arise when implementing smart houses, including cost-effectiveness, privacy, autonomy, informed consent, dignity, safety, and trust.
Conclusions: The identified ethical challenges are important to consider when developing smart house systems. Due to the limitations of smart house technology, designers and users should be mindful that smart houses can achieve a safer and more dignified life-style but cannot solve all the challenges related to ageing, disabilities, and disease. At some point, smart houses can no longer help persons as they develop needs that smart houses cannot meet.

Keywords: Assistive technology, Assistive living, Privacy, Ethical challenges, Norway

In the European Union, people aged 65 and older comprise 18.9 percent of the population, as of 2015, a 0.4 percent increase from 2014 and a 2.3 percent increase from 10 years earlier (1). Older adults account for 21.7 percent of the population in Italy, 21.0 percent in Germany and 20.9 percent in Greece (1). In Norway, adults aged 67–79 years make up 10.4 percent of the population, and those 80 years and older 4.2 percent as of February 2017 (2). The population projection in Norway predicts that in 2060, 19 percent of the population will be 70 and older, compared with the current 11 percent in 2016. These population trends are expected to continue (3) in the European Free Trade Association countries (EFTA: Iceland, Liechtenstein, Norway, and Switzerland), candidate countries (Croatia, Macedonia, and Turkey), United States, China, and Japan (1;4).

In Norway, 38.5 percent of households aged 65 and over consist of people living alone (3;5). As the older-adult population grows, so does the need for solutions to elderly housing. Smart houses can support those who desire to live in their own homes as long as they can care for themselves and, therefore, may be beneficial for older adults and people with disabilities (4).

Smart house commonly refers to any living or working environment carefully designed to assist residents in carrying out daily activities and to promote independent lifestyles (4). A smart house allows control of its functions and interacts with residents through voice, movement sensors, hand gestures, touch panels, and other options. A smart house usually adapts the house functions to the residents' preferences (4). The technologies used in the University College of Southeast Norway's (USN) smart house project include movement detectors, sonar, temperature sensors, weather stations, door and window switches.

A health technology assessment (HTA) is the systematic study of the consequences of technology use in a particular context (6). As health technology is intended to help people in everyday life, an HTA should also consider the moral issues affecting the people who use the technology in addition to issues more commonly assessed, as, for example, outcome and cost. As a response to the rather ad hoc assessments of the moral issues and ethical implications of health technology, Hofmann (6) developed a 33-point checklist for assessing ethical issues in a HTA. This collection of questions is eclectic and is not based on a particular moral theory and so has shortcomings. To the authors' knowledge, the ethical and moral implications of implementing smart house technology for older adults have not been systematically evaluated.

This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

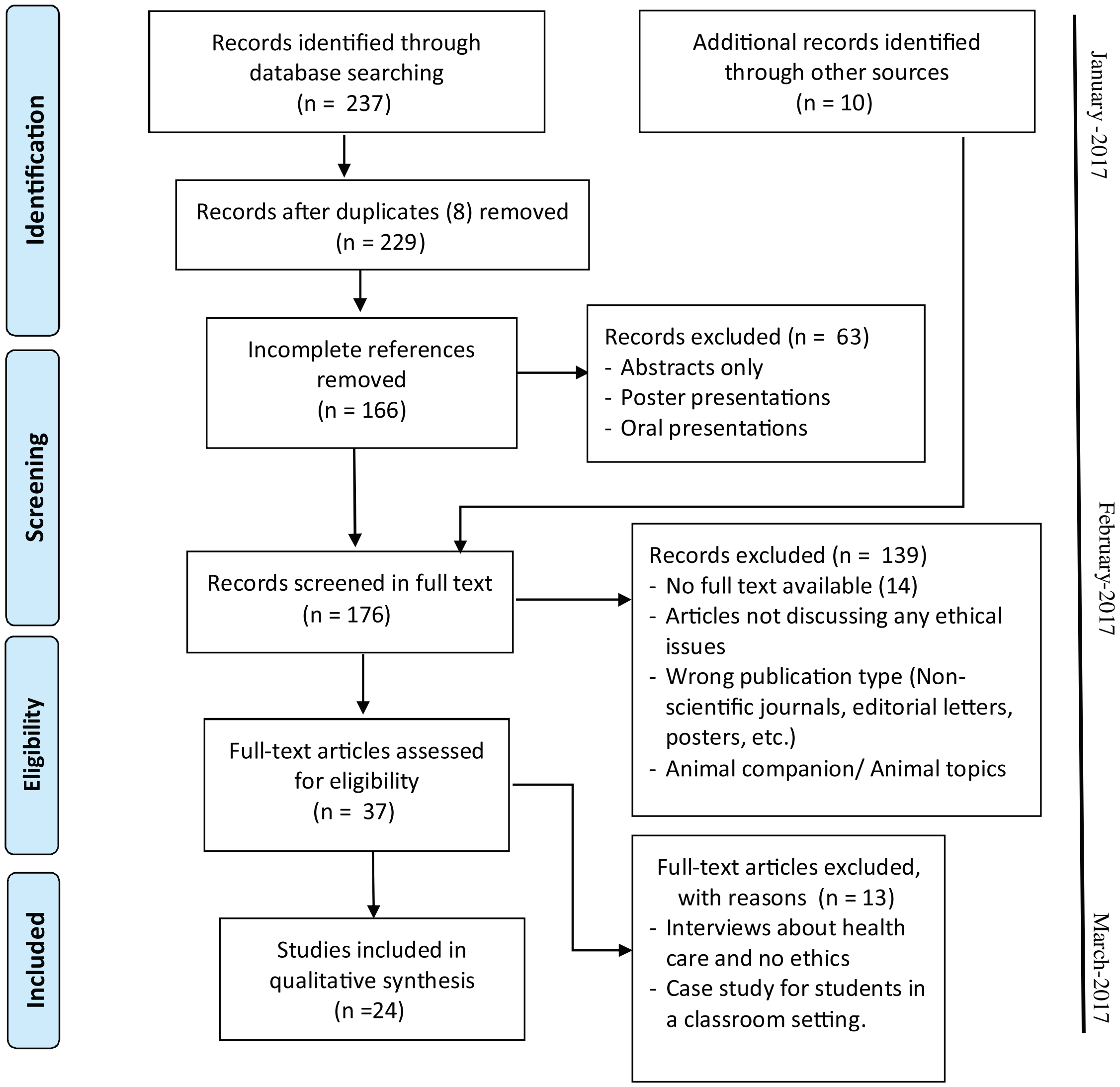

Figure 1. PRISMA 2009 flow diagram of the selection process.

METHODS

Aim

The study aim is to describe the ethical challenges when implementing smart house welfare technology for older adults.

Design

This study is a literature review reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (7). The PRISMA flow diagram is used to present the selected articles (Figure 1). The design of this review follows Hofmann's six steps for assessing ethical issues on Health Technology Assessment (6;8).

Search Process

The Academic Search Premier EBSCO, Medline, PubMed, Science Direct, and CINAHL databases were searched in January 2017 for peer-reviewed articles in English, French, Spanish, or Norwegian. Journal articles and conference proceedings were chosen. We used the following search terms: Smart home, smart house, assisted living, elderly, older adult, welfare technology, and ethic to identify all relevant papers. See Appendix 1.

Data Selection

The sample included papers that met the following criteria: (i) literature reviews on ethical challenges related to welfare technology; (ii) project assessments, including smart houses, assisted living and assisted housing; (iii) surveys describing user satisfaction with smart houses or assisted living equipment; (iv) articles on older adults; (v) articles in English, French, Spanish, and Norwegian.

The following exclusion criteria were applied: (i) duplicated studies, (ii) articles not discussing any ethical issues,

(iii) wrong publication type (nonscientific journals, editorial letters, posters, etc).

Data Analysis

Among the various HTA approaches to ethical issues (9), Hofmann's checklist (6) is used in this study to assess the moral and the ethical issues related to the use of smart house technology. Hofmann's checklist is an axiological question-based (Socratic) approach to ethics in HTA, and was chosen as it is well known in the literature on ethical issues (10). The researchers considered the following questions: (i) Which of the thirty-three questions in Hofmann's list do the articles address? (ii) Which issues addressed in these questions are raised throughout the literature? (iii) Which of the thirty-three questions in Hofmann's list does the literature reviewed not address?

Using Hofmann's questions checklist enables an explicit and systematic approach to the identification of relevant ethical issues found in the published literature. Hofmann's normative framework answers moral issues regarding stakeholders, technology, methodological choices, and technology assessment. The articles selected according to the inclusion criteria were appraised with a pragmatic approach. The articles were included if they presented results concerning the ethical considerations regarding smart houses for older adults and were published in scientific journals.

The identification of ethical issues were first done by the main author, but on several occasions corroborated with the other authors to achieve consensus.

RESULTS

Study Selection Results

The literature search identified 237 potentially relevant hits (Figure 1). After the first and second author screened all 237 titles, 8 duplicate articles, and 63 articles with incomplete references were discarded. The first author systematically read in full the remaining 166 articles, identified 27 potential references and read them thoroughly. Articles that clearly did not meet the inclusion criteria were discarded, leaving fourteen articles. Ten other records were found through other sources: article references, Spanish-language journals, and colleagues' recommendations. Finally, twenty-four studies were carefully read for findings concerning the research questions (Figure 1).

The selected articles were synthesized by answering each of Hofmann's questions (6). Thirty-one questions were answered, while the published literature offered no data for two questions. The authors answered Q29–Q31 as they referred to the authors' interests in conducting this review and could not be answered from the literature analysis. Table 1 shows the number of publications related to Hofmann's questions.

Moral Issues (Q1–Q16)

Q1. Smart houses raise ethical consequences concerning, privacy, autonomy, informed consent, dignity, safety, trust, legal obligations, and technology acceptance, among others (Table 2) (11–15).

Q2. Loss of autonomy is a recurrent concern regarding smart house technology (12;15;16). In smart houses, the "potential dependence on the technology may ultimately result in patients and caregivers" reliance on automation (16). However, the alternative of receiving care in nursing facilities might also entail giving up independence, resulting in similar loss of autonomy (17).

Another issue is sharing control in the cases of persons with disabilities (11). The question becomes who controls whom. (15). Too much support (12) or dependence on technology may reduce individuals' ability to control their environment (11;18). If the system changes individuals' daily lives or limits their freedom of choice in any way, then their independence and autonomy are restricted. Autonomy also entails willingness to use devices (15), including smart houses. Informed consent from participants can indicate willingness.

Q3. Smart houses can be subject to criminal use, and as such, may pose a threat to basic rights of integrity and safety (11). For example, unauthorized access to smart house data can enable blackmail and extortion.

Information about older adults' activities in their homes is powerful, and confidentiality must be ensured so that no third party can intercept individuals' data (4). The information includes patterns such as when a person gets out of bed, goes to sleep, cooks, eats and leaves the house alone (4;13). All this information is sensitive and can lead to misuse in the wrong hands. Poorly protected smart house systems can allow unauthorized third-party access, increasing the risk for identity theft and robbery (14). The network layer, communication protocols, and physical data storage, therefore, need to be secured.

Control over personal information is a right, and the European human rights framework promises "autonomy in the construction of one's identity" (11), but data leaks from smart houses can compromise these rights. The sensors installed throughout homes can also raise fear of surveillance, preventing older adults from engaging in some activities (12;15).

Q4 and Q5. Privacy is a central topic in smart house development (12;13;15). Several smart house welfare systems use cameras to support aging in place, detect where residents are and ensure safety by detecting falls (4). However, residents might have the sensation of being watched all the time and having no privacy. Older adults might "trade privacy for autonomy" (19). Thus, privacy can be compromised for persons in need of support (18;19).

The sensors used in smart house technology, including cameras, can transfer large quantities of sensitive information (11), creating tension between privacy and safety (19). People with higher risk of harm often require intense surveillance to

Table 1. Number of Publications Related to Hofmann's Questions

	Questions	No. of reports
Moral issues		
Q1	What are the morally relevant consequences of the implementation of the technology?	5
Q2	Does the implementation or use of the technology challenge patient autonomy?	6
Q3	Does the technology in any way violate or interfere with basic human rights?	6
Q4	Does the technology challenge human integrity?	8
Q5	Does the technology challenge human dignity?	5
Q6	Will there be a moral obligation related to the implementation and use of a technology?	1
Q7	Does the technology challenge social values and arrangements?	2
Q8	Does the widespread use of the technology change our conception of certain persons (e.g., with certain diseases)?	3
Q9	Does the technology contest religious, social, or cultural convictions?	4
Q10	Can the use of the technology in any way challenge relevant law?	4
Q11	How does the assessed technology relate to more general challenges of modern medicine?	6
Q12	Are there any related technologies that have turned out to be morally challenging?	4
Q13	Does the technology in any way challenge or change the relationship between physician and patient?	7
Q14	How does the implementation of the technology affect the distribution of health care?	4
Q15	How does the technology contribute to or challenge professional autonomy?	2
Q16	Can the technology harm the patient?	3
Questions with respect to stakeholders		
Q17	What patient group is the beneficiary of the technology?	14
Q18	Are there third-party agents involved?	4
Q19	What are the interests of the users of the technology?	3
Q20	What are the interests of the producers of technology (industry, universities)?	5
Questions related to technology		
Q21	Are there moral challenges related to components of a technology that are relevant to the technology as such?	7
Q22	What is the characteristic of the technology to be assessed?	1
Q23	Is the symbolic value of the technology of any moral relevance?	9
Moral aspects of methodological choices		
Q24	Are there morally relevant issues related to the choice of end points in the assessment?	3
Q25	Are there morally relevant issues related to the selection of studies to be included in the HTA?	1
Q26	Are the users of the technology in the studies representative of the users that will apply it in clinical practice?	3
Q27	Are there morally relevant aspects with respect to the level of generalization?	2
Q28	Are there moral issues in research ethics that are important to the HTA?	2
Questions related to technology assessment		
Q29	What are the reasons that this technology is selected to be assessed?	0
Q30	What are the interests of the persons participating in the technology assessment?	0
Q31	At what time in the development of the technology is it assessed?	0
Q32	Are there related technologies that have or have not been assessed?	0
Q33	What are the moral consequences of the HTA?	0

Note. The number on the right refers to the total number of publications found for each question. The publications were identified by assessing ethical issues related to Hofmann's question list.

avoid unsafe situations (18). Privacy can be increased by ensuring the anonymity of the collected data (12) and by obtaining informed consent and voluntary use (15;19). It is worth noting that informed consent should be regarded as an on-going process and not a singular event (16).

Another issue is individual independence, or living in one's own home and self-reliant from caregivers or nursing facilities (12). Definitions of independence may vary among individuals. Tracking technologies can create more secure environments for people with cognitive disabilities and reduce the distress

Table 2. Number of Publications Related to the Main Ethical Challenges

Ethical challenges identified	Number of reports
Cost-effectiveness	9
Privacy	8
Autonomy	7
Informed consent	6
Dignity	5
Safety	5
Trust	5
Legal Aspects	4
Technology acceptance	4
Exclusion, depression, and isolation	4
Reduction of human contact	4
Gap between designers and users	4
Technology testing/assessment	3

of their families and caregivers (20). However, tracking may undermine older adults' independence, giving rise to ethical questions: when is such technology helpful, and when does it violate older adults' dignity (21)?

The smart house context can also challenge individuals' freedom to do as they wish (18). Forced care for the older adult and the wish to safely care for them (using smart houses) can produce tension. Older adults may become passive regarding the technology, which can be mistaken for acceptance (18). There is a difference between doing tasks *for* the older adult instead of *with* them (or helping them to do the task). Doing tasks *for* them can violate their physical independence and control over their environment (18). This may result in passive acceptance and autonomy loss (Q2).

Technology dependency especially affects people with disabilities, who might believe that their existence is no longer the same and that their functions are restricted by the technology (15). Furthermore, healthcare personnel and smart house designers act as experts on individuals' needs, disregarding their autonomy (15).

Q6. Smart houses carry the risk of failure, particularly in system maintenance and false alarms. Delegation of control, therefore, is a moral obligation (11). Who will deal with false alarms should be decided when deploying a smart house. The party responsible for false alarms should be a person capable of giving informed consent.

Q7, Q8, and Q9. Overall, smart houses should bring peace of mind to older adults and their families. Smart houses provide a safer environment, reduce risks, avoid harm (e.g., falling or fire) and decrease utility costs, among other benefits (22). For some older adults, smart houses may offer more privacy than cared from relatives. For instance, one older adult expresses that she prefers a monitoring system, rather than her son knowing all her "business" (19).

Many prospective users, however, perceive smart house technology negatively due to cultural beliefs (15;21) (Q9) and social barriers to assistive technology. Some older adults might fear that their relatives' or caregivers' perceptions will change if they start using assistive technology (21). For example, technology should improve older adults' safety by preventing and detecting falls (12). However, the need to look after older adults is reduced, so safety could be compromised if the system fails to detect a fall. Moreover, marginalization of older adults can increase due to tracking or alternative communication which highlights their disabilities (15). This marginalization may result from negative cultural beliefs or stereotypes. Finally, a shift from a patient-centered to a family-centered approach occurs, and the impact of home monitoring on family caregivers has not yet been fully studied (21).

Cost-effectiveness is a challenge for smart houses whose high costs tend to be unaffordable for prospective users (11). Designers, therefore, should keep in mind costs to allow more people to benefit from the technology (21). Cultural differences and backgrounds also play significant roles in the acceptance of smart houses and implementation phase (23). In some cultures, household heads make decisions, even for individuals capable of consenting (15;21). As well, the ethical framework applied to the design, evaluation, and implementation of smart houses varies by country (21). Legal and regulatory environments have national differences. A smart house designed in a specific country, therefore, should not be used as-is in another country but should undergo testing for any cultural and social issues that might arise (21).

Q10. Legal frameworks view the home as a private space, but smart house systems which collect personal data threaten privacy (19). Controls on data collection by smart houses should be in place and stipulate how long and in what form data about residents may be stored (11). Another issue is potential legal liability for fewer nurse and doctor visits to older adult (11;12). Legal responsibilities, therefore, are a concern. French norms hold that home-support technology needs to be subject to standards and principles of quality. In addition, French law and the Council of European Communities regulate responsibility for making defective home-support devices (24).

Q11 and Q12. Despite the original purpose of smart-home technology, the technology has been demonstrated to lead to exclusion, depression (11;15;25), the feeling of losing control over one's own life (Q13) (26), and loss of autonomy (Q2) (12;15;16). Some technology devices, such as tracking devices and cameras, have already been introduced in the field of elderly care (26). Surveillance cameras are perceived as obtrusive and violating individual privacy (Q4) (4). Older adults prefer less intrusive cameras that do not identify people, such as cameras with fuzzy silhouettes (13). As well, the introduction of technology to older adults does not always proceed smoothly, as in the case of Internet access (21). If Internet safety is not taught, older adults run the risk of falling prey to scams, phishing, and other security issues.

Q13. The impact of human interaction on individuals' life is another ethical challenge. Technology may replace or diminish older adults' human contact, leaving them with 24-hour, sensor-based technology and reducing their opportunities for meaningful social engagement (4;17). It is important to ensure that technology does not replace human contact and result in isolation (11;15). Social isolation is regarded as detrimental to older adults' social well-being and should be avoided (12).

Smart houses might eliminate the need for doctors and relatives to constantly check in on older adults, who also might not need regular doctors' visits (4;16). Monitoring of older adults in their own homes can provide constant data about their activities for doctors and caregivers, increasing older adults' feeling of safety (21). Nevertheless, technology should not replace physicians (21). Reduced communication between doctors and patients can result in negative health consequences.

Q14. The growth of the older-adult population will create greater "need for nursing home beds or an adapted dwelling" (27), pressure on healthcare cost, dependency among older adults and caregiver shortages (28). In 2012, Norway saw increased investments in care services in preparation for the upsurge in the older population (27). In 2016, Norway had 40,708 beds available for older adults, while 232,350 people used home help, home nursing or other home-based serviced (27). Smart houses with monitoring (19) can allow older adults to remain at home instead of moving into nursing homes as "institution beds have been getting replaced by dwellings with full-time home services for many years" (27). Smart houses can also decrease the number of healthcare personnel needed by patients. From the perspective of the healthcare system and personnel costs, smart houses are important investments but are available only in highly developed countries (15).

Q15. Smart house technology involves professionals in several fields, including social, technical and clinical fields. At one time, doctors even feared that machines would replace them (21). In the design phase, engineers aim to create smart houses that make decisions and ease users' lives, healthcare personnel expect the technology to support them (15), and physicians make decisions and assess patients based on technology-generated data. In this scenario, the professional's autonomy dominates, and the patient's autonomy is reduced, especially for individuals with disabilities (15).

Q16. Technology is not neutral, and risk and harms can occur when using smart house technology. The harms include undetected falls, navigation problems (while using tracking), unattended events and other issues that compromise older adults' safety (12). Smart houses, though, are intended to improve older adults' quality of life so that they tend to feel safer, to see themselves as "in good hands" and to not need caregivers to the same extent (21). This feeling can be beneficial or detrimental to safety depending on the person. Confidence in the smart house to care for the older adult can make the caregiver think that the patient has no need for the caregiver. This is a major problem in smart houses designed for people with Alzheimer's, who can encounter dangerous situations (21). Another possible harm is frustration generated by technology use, such as a frequent need to change batteries or reset the system (21). A smart house designed for older adults should be kept simple, and special attention should be given to training and support (28).

Questions with Respect to Stakeholders (Q17–Q20)

Q17. Some smart houses are aimed at the third-age population (4;12;13;15–21;23;24;26), retired persons who are alert and in full possession of their physical and mental capacities (29). Other smart houses are intended for the fourth-age population, the elderly who have reduced functional autonomy and depend on external resources to ensure good living conditions (29). The role of smart houses in the third-age population has not yet been established. However, older people have specific needs that can be challenges in technological development. Older adults should have the right to live independently at home for as long as possible and have access to assistance services (29).

Q18. Identifying the direct and the indirect stakeholders and "all [the] parties from whom consent must be sought" is important (16). Smart house systems handle sensitive information (Q6) (4) which should be encrypted throughout the system to prevent access by third parties (14). It is, therefore, important to ensure that those with access to the information protect confidentiality (4), fully understand the situation, and cannot misuse the information (14).

Older adults can decide with whom to share the information collected by the system (14). They have been found to be willing to share the system information with relatives but concerned about how their relatives will perceive their behaviors, such as "erroneous but explainable behavior" (13). Who may access sensitive personal information and who may make decisions regarding the information content should, therefore, be determined.

Q19. Some older adults prefer to have an "infrastructure-sensing technology" (13) rather than move into nursing homes or have constant checks from caregivers (4;16). A possible explanation for this preference is that the technology is not completely visible and thus not a persistent reminder of adults' frailty (13).

Q20. The Norwegian government has invested in the development of smart houses for older people (30) based on the view that "care of older people is a public responsibility" (31). Moreover, care workers are "increasingly subjected to time pressures" and do not have sufficient time to deliver high-quality care to older adults (31). Care workers experience frustration when they cannot provide proper, essential care to older adults (31).

Norway's national policy is "to support older home care for as long as possible" to reduce national healthcare expenditures (32). The government supports nursing homes but requires older adults to pay 75–85 percent of their income for nursing care, creating an economic burden for families. Living at home rather than in nursing facilities, therefore, saves costs (4). In addition, the report by Fjelltun et al. (32) describes the ethical issues and problems involving decisions on nursing home placement and availability. Regarding the interests of the technology producers, it is important to be transparent and to "disclose all sources of commercial and public research funding" to avoid bias in the findings (21).

Questions Related to Technology (Q21–23)

Q21, Q22, and Q23. In general, smart houses should learn from residents' activities and behavior and adapt to their needs (4). This enables detecting anomalies, which refers to finding patterns in data that do not follow normal or expected individual behavior (28). However, the system designers rather than the users establish anomaly detection, leading to data interpretation from the designers' perspective and limiting individuals' privacy and freedom of choice (11;15). In addition, the designers set the functions of smart houses (12).

Consequently, the designers play a key role in the development of smart houses that can affect users positively or negatively. The designers must take into account who the consumers are and what they need and understand their cognitive impairments and disabilities (21). A gap, however, exists between the designers' values and the ethical implications of designing smart houses for older adults (12), giving rise to ethical issues such as privacy, autonomy, dignity, integrity, and cost effectiveness (4;11–15;21). User feedback should be sought during the research and development (R&D) stage to reduce possible errors in the product (23). Potential users not involved in the R&D phase might reject new technology (15) (Q7). Designers, therefore, should consider that older people face many age-related problems, such as limited physical activities, hearing, vision, and cognitive decline (28). A study on fifteen older adults' perceptions and concerns about smart homes suggested various benefits (33): emergency help, stove and oven safety control, property security, intruder alarms, automatic lighting, assistance with hearing and visual impairments, prevention and detection of falls, temperature and physiological parameters monitoring (e.g., blood pressure and glucose levels), reminder system for upcoming appointments or events, and timely, accurate information on adverse drug events, and contraindications.

Moral Aspects of Methodological Choices (Q24–Q28)

Q24 and Q25. Smart houses are generally assessed for older adults and people with disabilities and cognitive impairments. Q25, Q26, Q27, and Q28 address testing of technology and the associated ethical challenges (15;21;26). Smart house technology falls within the field of information and communication technology (ICT), not medical technology. Consequently, smart houses and devices (e.g., tracking devices, cameras, and alarms) to support independent living are not always tested to the same standards as clinical medical research involving humans (26). This lack of ethical research procedures raises ethical challenges that need to be considered before fully implementing smart houses (26).

Q26 and Q 27. The articles found suggest that the technology users are representative of the final users. The articles on technology testing, however, urge checking cultural differences (Q9) (21). The participants (testing and final consumers) should be informed that the benefits of technology might vary between individuals (26) (Q27). A review of the guidelines for trials of older-adult care stipulate that when trials of elderly home care involve persons with disabilities or older persons at risk, the participants should be informed that they might not derive any personal benefit from the research (26). The participants in testing are not always "fully informed about the purpose of the work" (26). It is, therefore, suggested that the participants and their relatives be informed about the costs and recommended use of assistive technology (15). Finally, when testing with people with cognitive impairments, the participants and their families should not be given false hope. Instead, the researchers should inform them of the study limitations and possible results (21).

Q28. Several elderly home-care projects target people with cognitive impairments, who constitute a special case when testing ICT devices in the home (26). Obtaining informed consent from them can be difficult but should not be overlooked. An "appropriate surrogate" can provide informed consent (21). In addition, the researcher in charge of smart house testing should ensure that the participants' autonomy and respect are protected, not dismissed (21).

Another challenge is that testing technology can go wrong, but no standards on how to deal with expenses or compensation to participants exist (26). However, if testing assistive technology proves to be beneficial to the participants, it can be ethically challenging to stop the trial and return the participants "to the[ir] original state" (26).

Questions Related to Technology Assessment (Q29–Q31)

Q29, Q30, and Q31. Smart houses offer a promising way to improve access to home care for older adults and people with disabilities. Given the importance of this project, it is essential to study its ethical impacts on users and the population in general. The authors' motivation for conducting this review is an on-going project at the USN. Other smart house technology projects have been undertaken, but most do not assess the ethical challenges presented by this technology. The authors decided to assess smart house ethical challenges during the development phase. Acknowledging and understanding these issues will help designers reduce their negative impacts.

DISCUSSION

The ethical challenges that arise when developing and implementing smart house technology need to be addressed before deployment. To identify these issues, Hofmann's normative framework of thirty-three questions was answered by synthesizing data in the published literature. Two questions could not be answered due to a lack of information (Table 1).

The published literature does not always directly mention smart houses but uses terms such as *assisted living* and *monitoring for older adults*. Nevertheless, the ethical challenges identified are related to similar technologies (e.g., cameras, tracking devices, and assistive devices). The recurrent ethical challenges include cost effectiveness, privacy, autonomy, informed consent, dignity, safety, and trust (Table 2).

Some of these challenges may be difficult to overcome. Increased autonomy is among the most persistent promises concerning technology designed for people with cognitive and physical disabilities. The benefits of smart houses, however, could also diminish personal autonomy. The literature suggests that in some cases, obtaining informed consent can overcome this challenge. Nevertheless, it should be acknowledged that solving this ethical challenge is difficult as there is a fine line between improving and limiting individuals' lives.

Another issue is the interests of the technology producers. Governments, designers, healthcare systems and consumers share a common goal to offer older adults opportunities to live at home more independently. However, the stakeholders might have different views on how to achieve this goal. Consequently, the dignity and the integrity of the individual are sometimes overlooked.

In addition, older adults' privacy can be compromised, and their freedom limited. Privacy-management policy is very important to address in smart house development due to the invasive nature of surveillance in homes. If older adults are to accept these systems, it is crucial to mitigate the invasion of privacy. Encrypting databases and securing the systems' communications can help provide privacy. Cameras can also use fuzzy silhouettes to avoid identifying persons.

Regarding the legal framework, countries have different laws regulating aspects of smart house technology. A review describes the legal challenges regarding data privacy, data management, stakeholders' interests, and informed consent in the Norwegian context (34). However, the standardization, research and assessment of the legal aspects of smart houses need to be addressed in an international perspective.

Finally, this review attempts to address the moral issues found in the literature using Hofmann's question list. The selection of moral issues presented in this review is meant to be impartial. The authors' interest is to understand these ethical challenges and consider them during the development phase of USN's smart house project.

Limitations

The main limitation of this literature review is that the methodological quality of the selected articles is not completely clear. Several of the articles do not report the research methodology, possibly because technology articles do not always report details of the research methodology.

Conclusion

The older population is growing in Norway, as well as other European countries. Demand and supply of nursing-care homes present a near-future challenge. Smart house technology offers a solution and could meet demand by allowing older people to remain in their homes for as long as possible. Nevertheless, ethical challenges demand consideration to ensure safe, dignified lives for older adults and people with disabilities.

Acknowledging the ethical challenges identified in this review is important for developing and implementing smart-house technology. Minimizing their impacts could boost acceptance of smart houses among older adults. However, smart-house designers and users should be mindful that this technology cannot solve all the problems or meet all the needs of older adults but can help them achieve more comfortable lifestyles. This systematic HTA of smart houses is intended to support universities and other technology producers by providing a comprehensive study on the relevant moral issues.

SUPPLEMENTARY MATERIAL

Supplementary Appendix:
https://doi.org/10.1017/S0266462317000964

CONFLICTS OF INTEREST

The authors have nothing to disclose.

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Appendix: Search strategy Ethics of smart-house welfare technology for older adults—a systematic literature review

Performed by Veralia Gabriela Sánchez, University of Southeast Norway, Porsgrunn
Performed: 11.01.2017

Databases

The Academic Search Premier EBSCO, Medline, Pubmed, Science Direct and CINAHL.

Search Strategy

The Academic Search Premier EBSCO, Medline, CINAHL

S1. Smart Home
S2. Smart House
S3. Assisted living
S4. Elderly
S5. Older adult
S6. Welfare technology
S7. Ethic*
S8. S1 OR S2 OR S3
S9. S4 OR S5
S10. S8 AND S9 AND S7

The search term Welfare technology (S6) was removed in the final search (S10) because the results returned "0" if it was used. The search was limited to articles from 2000 to present.

The following results were obtained:

EBSCO (83) + Medline (11) + CINAHL (8) = 102

Sciencedirect

Results = 132

Search strategy: "(Smart home OR smart house OR assisted living) AND (elderly OR older adult) AND welfare technology AND ethic*"

The search was limited to Journals only from the year 2000 to present.

Pubmed

Results: 3

Search strategy: "(Smart home OR smart house OR assisted living) AND (elderly OR older adult) AND welfare technology AND ethic*"

Total:

The searches resulted in 237 references as follow:

EBSCO (83) + Medline (11) + Pubmed(3) + Sience Direct (132) + CINAHL (8)=237

Journal Article 4

Older People's Attitudes And Perspectives Of Welfare Technology In Norway

Sánchez, Veralia Gabriela, Camilla Anker-Hansen, Ingrid Taylor, Grethe Eilertsen

Journal of Multidisciplinary Healthcare (2019)

DOI: 10.2147/JMDH.S219458

Journal of Multidisciplinary Healthcare

Dovepress
open access to scientific and medical research

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ORIGINAL RESEARCH

Older People's Attitudes And Perspectives Of Welfare Technology In Norway

This article was published in the following Dove Press journal:
Journal of Multidisciplinary Healthcare

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Background: In Norway, as in other European countries, the ageing population is increasing rapidly. Governments seek to enable older people stay in their homes for as long as possible, and welfare technology (WT) has been proposed as a possible solution. Human behaviour modelling (HBM) is a welfare technology that identifies an individual's behaviour patterns and detects abnormal behaviours, including falls and early signs of dementia. However, the successful development of HBM WT requires the consideration of the older people's attitudes on this.
Aim: The present study sought to explore attitudes and perspectives about welfare technology among older people living alone in Norway.
Methods: We used an exploratory, qualitative approach in which semi-structured, in-depth interviews were conducted with five women and four men between the ages of 79 and 91. The interviews were analysed using qualitative content analysis.
Results: Two categories and four subcategories were identified: 1) preferences and concerns of welfare technology (i) feeling confident-proactive approach of future technology, (ii) concerns and dilemmas, and 2) reflections of today and tomorrow- awareness of own health (i) feeling healthy, independent, self-sufficient and safe, (ii) facing own ageing- preparedness on unpredictable scenarios. The main theme, welfare technology - a valuable addition to tomorrow's homes, represents how the participants held positive and proactive attitudes towards the use of WT in their homes.
Conclusion: Participants trusted the Norwegian healthcare system and did not rely on their families for care. Independence, autonomy, and feeling safe were essential for all participants, and most participants regarded welfare technology as empowering them to remain in their homes for as long as possible. Participants already confidently used various technologies in their daily lives. Surprisingly, they expressed no concerns about privacy, but some mention concerns about loss of autonomy and dignity. We conclude that a person-centred approach to integrating new WT is necessary.
Keywords: assistive technology, ambient assistive living, ethical challenges, healthcare, ageing in place, human behaviour

Introduction

In Norway, as in other European countries, the proportion of older people in the population is increasing rapidly. In the European Union, 12.7% of the population will be 80 or older by 2080, compared to just 5.5% in 2017.[1] Furthermore, in Norway, 38.5% of people aged 65 and over live alone.[2]

Norwegian municipalities are obligated to provide healthcare services for older people, including home healthcare, practical assistance with daily tasks, and, if needed, nursing homes.[3,4] Healthcare services are regulated by the Norwegian

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http://doi.org/10.2147/JMDH.S219458

Municipal Health and Care Service Act of 2011, and anyone living in Norway has the legal right to access necessary healthcare services.[5]

The need for nursing and healthcare services in Norway increased by 18% from 2007 to 2017.[6] The Norwegian nursing association has reported that there is a shortage of 6,000 nurses at present projected to increase to 30,000 in 20 years.[7] People living in large cities often have to wait longer to receive care services than people in less populated areas.[4] Given this increasing shortage and the fact that people are living longer, several studies have concluded that the Norwegian state will not be able to cope with rising demand for eldercare services, creating a need for more nursing homes.[3,8–10] However, nursing home availability in Norway also decreased by 2% from 2015 to 2018.[11]

Furthermore, the ability for older people to stay in their own homes, also known as ageing in place, presents many advantages compared to moving to residential care facilities. Studies in Europe and New Zeland[12–14] have shown that remaining in a familiar environment increases independence, is cost-effective, decreases the risk of contracting infectious disease, and helps individuals cope with the shortage of healthcare. Enabling older people to remain in their homes for as long as they are in good health and can take care of themselves has therefore been a stated goal of the Norwegian state for the last 70 years.[15,16]

New solutions are therefore needed that allow older people to remain at home. In addition, as life expectancy increases, so does the need for staying healthy while ageing.[17] Welfare technology, defined as 'technology used for environmental control, safety and wellbeing, in particular for elderly and disabled people'[10] (and more often referred to as 'ambient assisted living' outside of Scandinavia), can contribute to facilitating sustainable healthcare for older people.[18,19] Its general goal is to construct technological solutions that enable a better and safer environment for older people and people with disabilities. Moreover, previous studies have shown that welfare technology increases older people's abilities to age in place and is regarded as good care that meets older people's needs and is easy to use.[20] Welfare technology can also help enable older people to remain healthier while ageing in place.[21] It is thus consistent with the goals of health promotion, which is defined as 'the process of enabling people to increase control over and to improve their health'.[22] The Norwegian government has therefore invested in welfare technology, including digital safety alarms, electronic door locking, digital supervision, nurse call systems, electronic pill dispensers, and 'smart houses'[6,23,24]—that is, living environments that have been designed to assist residents with their daily activities and to promote independent lifestyles.[8,25]

Nevertheless, ageing in place also carries risks, including health deterioration and safety issues like falls and dizziness.[13] Human behaviour modelling (HBM) is a type of welfare technology that can recognise an individual's behaviour patterns in a smart house, thereby helping to construct a safe environment. HBM aims to detect abnormal behaviours, such as falls and early signs of dementia, in order to alert family members or a caretaker if assistance is needed. The concept is based on an assumption that individuals tend to follow recognisable patterns in their daily lives,[26,27] thereby making it possible to predict their future behaviours and actions. However, welfare technology that can detect human behaviour in this manner is relatively new, and research is still sparse.[28–32]

Studies have shown that it is important to consider end-users' feedback from the beginning of the research and development stage, in order to avoid their later rejection of the developed technology.[8,33] This is also consistent with the person-centred research principle of keeping individuals' values central to decision-making.[34] Technology contributes to changes in relationships; in the case of older people, in particular, this affects not only their social lives but also their healthcare practices, thereby introducing new risks and ethical questions.

The person-centred research perspective emphasises the necessity of respecting the individual[35] and seeks to study 'how technology influences relationships […] and how it contributes to humanistic values or diminishes them',[19] with the ultimate goal of developing a final product that is genuinely useful to end-users—in this case, older people.[17,36] Older people who live alone stand to benefit the most from welfare technology, including HBM, and in order to plan for and create a sustainable and targeted healthcare solution for them, it is important to understand their attitudes to welfare technology which is underpinned by person-centred principles.[34] However, there has been limited attention to this topic.

Aim And Research Question

The aim of this study is to explore older people's attitudes to welfare technology. The research question is as follows: What characterises the attitudes of and experiences with welfare technology among older people living alone in Norway?

Design And Methodology

This study used an explorative, qualitative design[37] with semi-structured interviews that followed the principles stated by Kallio.[38] The data were analysed using the content analysis method described by Graneheim and Lundman.[39]

Recruitment Procedure And Sample

Two strategies were used to recruit participants. A first recruitment was done through criterion sampling, which consists on selecting participants that meet predetermined inclusion criteria;[40] living alone; being older than 75 years old; speaking Norwegian, English, or Spanish; and not receiving any kind of public healthcare services. E-mails and letters were sent to five different interest organizations of retired people, without having positive responses. One organization did not have time for distributing information, the other four organizations did not responded. Consequently, an informational poster describing the project and criteria was posted in a senior centre in south-east Norway. Two participants were recruited by this procedure.

Due to the lack of responses and the slow recruitment, snowball sampling was implemented as an additional recruitment procedure. This approach involves asking knowledgeable people about whom could participate. As described by Patton,[40] ‘by asking a number of people who else to talk with, the snowball gets bigger and bigger as you accumulate new information-rich cases’. One of the researcher contacted the leader of an interest organisation of older persons, the knowledgeable person, to inform about the study. This organisation leader then informed a fellow member, who informed others, resulting in seven participants. Thus, the two recruitment procedures resulted in a total of nine participants.

The data were collected from May 2017 to January 2018, in the south-eastern region of Norway. The final sample comprised five women and four men between the ages of 75 and 91, where all of them were retired (Table 1). No more participants were recruited because we assessed the collected data to be rich enough[41] to answer the research question. Marshall[42] states that 'in practice, the number of required subjects usually becomes obvious as the study progresses, as new categories, themes or explanations stop emerging from the data (data saturation)'. Additionally, qualitative research sampling has no fixed minimum nor maximum number of participants and hence the sample may involve small numbers of participants and large amount of data collected. The most important is that 'sufficient depth of information is gathered to fully describe the phenomena being studied'.[43]

Data Collection

Since welfare technology that can detect changes in the person’s behaviour, such as HMB, is still in the research stage, before each interview the researcher explained to the participant how such technology would work. Each interview then began by exploring the participant’s prior experiences with other welfare technological devices, and these responses formed the background for the present study.

Based on a thorough examination of earlier studies[44] and in line with the aim of this study, an interview guide was developed and pilot-tested with a volunteer. After the pilot test, some minor adjustments were made based on the volunteer’s responses. Figure 1 shows the semi-structured interviews guide. In addition to demographic data, including family and community information, three broad themes of inquiry were investigated: 1) reflections on safety issues, 2) experiences with and attitudes towards welfare technology, and 3) experiences with and attitudes towards privacy issues. The interview format sought to invite open dialogue and used open-ended questions, for

Table 1 Demographic Characteristics

Participant	Gender	Age	Civil status	Type Of House	Years Living Alone	Years In Current House
P1	Female	91	Widow	Senior apartment	No data	22 years
P2	Male	79	Widow	Own house	2 years	49 years
P3	Male	80	Widow	Senior apartment	6 years	2 years
P4	Male	79	Widow	Own house	14 years	14 years
P5	Male	79	Widow	Own house	1.5 years	No data
P6	Female	83	Divorced	Own house	60 years	13 years
P7	Female	84	Widow	Apartment	11 years	20 years
P8	Female	84	Widow	Own house	10 years	52 years
P9	Female	89	Widow	Senior apartment	16 years	7 years

A. Introduction- About yourself

1. Participant reflecting on their daily life[44]
   - I. Can you tell us about your daily routine? What do you usually do?
2. About their moving during life:
   - I. How long have you lived here?
   - II. Would you be comfortable moving to another house?

B. Family and Network

1. About your family
   - I. Do they live nearby? [44]How often do they visit you?
2. Your social life
   - I. How is your social life? Any hobbies?
   - II. Do you get visits from friends? How often?
3. About your neighbors:
   - I. Do you know your neighbors?
   - II. Are they older adults? Families?

C. Safety

1. Do you think about safety? In what way?
2. Let's talk about your home[44]
   - I. Do you feel safe in your house?
   - II. We all do things that make us feel safe. Is there anything you do to feel safer?
   - III. Is there something that makes you feel unsafe?
   - IV. Is there something you think you need to make your daily life safer?
   - V. Do you think technology could help you feel safer or have any other benefit for you?
     - a. How can we (with technology) increase the safety of your house?
3. Is there anything that is a threat to security in your home? (ex. Carpets, stairs, low lights)
4. Do you have any challenge living by yourself? Being alone/feeling lonely?

D. The system and perceptions of technology

1. What do you think about the idea of the system that could let your family know if there was something wrong?
2. What do you think about a system that could detect change in your daily routine? (early signs of dementia, falls)
3. Who would you like to have responsibility for the alarms/system/access to the data? (Ex. care worker, family member.)
4. Do you prefer to have home nursing care (hjemmesykepleie), home care (hjemmehjelp) or a welfare technology system?
5. What do you think is important for you to stay at home for as long as possible?

E. Privacy

1. If I say privacy, what kind of things do you think about?[44]
2. Would you prefer to have a caretaker/family member or technology to check in on you?
3. Are there things that you like to keep private from your family?
4. What kind of dilemmas do you see in technology?
   - I. Do you think technology would interfere with your freedom?
   - II. Would you stop doing something if you had a welfare technology system?
5. What do you think about having a camera in your home?
6. What do you think about having a bracelet that can detect falls, and create an alert?
7. Is there anything else you want to add concerning what we have been talking about?

Figure 1 Semi-structured interview questionnaire guide.

example about participants' prior experiences with technology and reflections on welfare technology. Questions such as 'Could you tell me about some experiences you have had with any technological devices?' and 'Could you describe [prior statement] even more thoroughly?' encouraged in-depth responses.

Interviews were conducted in each participant's own home to help participants visualise their circumstances and reflect about the questions based on their current lived experiences at home, for example about whether their home had any stairs or carpets that could be tripping hazards. All but one of the interviews were digitally recorded and transcribed verbatim; due to one participant's request, manual field notes were instead used to record one interview. The interviews ranged from 45–75 mins in length.

Data Analysis

One interview was randomly selected for initial analysis by all of the authors. Its content was analysed using the method described by Graneheim and Lundman[39] who defined content analysis as an analysis of both the manifest content and of the interpretations of latent content. Manifest content is that which is written explicitly, while latent content refers to what the text implicitly addresses. The interpretation of latent content during analysis is thus a 'co-creation of the researchers and the text', and thus the 'data and interpretation are co-creations of the interviewee and the interviewer'.[45,46]

The analysis of the first interview started by every member of the research team individually identifying 'meaning units'—i.e., words, sentences, or paragraphs on the same topic. The meaning units were then condensed and codified, followed by preliminary suggestions of sub-categories topic (Table 2). After all members of the research team had discussed and agreed on the preliminary analysis of the first transcript, the eight remaining interviews transcripts were analysed by VGS following the same procedure. All transcriptions were read several times by all members. A total of 52 codes were identified and thoroughly discussed by the research team. After unanimous consent, the codes were then grouped into subcategories of topics that shared similarities.[47] This process continued until the final analysis could be summarised as a single theme, with two main categories reflecting the manifest content of the subcategories. Table 3 shows the four main analytical steps drawn during the data analysis with the corresponding number of meaning units, codes, sub-categories and categories for each step. Between analysis step 2 and 3, the total of 366 meaning units were

Table 2 Example Of The Analysis Procedure From A Manifest To A Latent Level

Manifest Level		**Latent Level**		
Meaning Units	**Condensed Meaning Unit**	**Code**	**Sub-Categories**	**Categories**
There is a nurse that comes just to deliver pills to my neighbour four times a day, it is not nice, but it is worse to have a machine for that	Home care nurse delivering pills is better than technology	Technology care should not replace human care	Concerns and dilemmas	Preferences and concerns of welfare technology
I am very careful, **I** always have my mobile in my night table and with me, even when **I** go to the bathroom in the night just in case **I** could fall or anything happens	Carrying phone to be able to call in case of emergency or falling	Having an action plan in case of emergency	Facing own ageing- preparedness for unpredictable scenarios	Reflections of today and tomorrow-awareness of own health

Table 3 Number Of Meaning Units, Codes, Sub-Categories And Categories Throughout The Four Main Analysis Steps

	Meaning Units	Codes	Sub-Categories	Categories
Analysis 1	981	85	19	4
Analysis 2	981	76	13	4
Analysis 3	615	52	7	3
Analysis 4 (Final)	**615**	**52**	**4**	**2**

reduced from the initial list. When the team worked through the list together, several of the meaning units were assessed to be either not relevant to the research questions or could be merged together. Examples of meaning units of no relevance could comprise information like 'I used to work a lot outside, like farming', 'I moved a lot before settling here'.

The findings were thus discussed in depth by all members of the research team until consensus was achieved. Categories were then compared in reverse with the manifest text to verify their accuracy and trustworthiness, using the trustworthiness criteria established by Lincoln and Guba:[48] credibility, transferability, dependability, and confirmability. In the present study, credibility was achieved through prolonged engagement and analyst triangulation; transferability was established by providing detailed descriptions that could be applied to other contexts; dependability was assessed using stepwise replication and a code-recode strategy to ensure that the findings were consistent and replicable; and confirmability was assessed using reflexivity throughout the analysis process and in consecutive discussions among the research team.

Ethical Considerations

All participants received verbal and written information from the interviewers about the project before proceeding to the interviews. Eight participants signed an informed consent form to participate in the study, while one participant gave oral informed consent. Confidentiality and anonymity were assured; no names were used in the transcriptions nor in the present study. Participation was voluntary and no economic compensation was given. The study was reported to the Norwegian Center for Research Data (NSD, project number 53841). NSD does not approves projects but they must be notified about the processing of personal data in the project, even if only anonymous data is published.[49]

Results

The analysis revealed a theme, two main categories and two sub-categories, presented in Table 4 below.

Preferences And Concerns Of Welfare Technology

Feeling Confident - Proactive Approach To Future Technology

All but one of the participants expressed a positive response to the idea of HBM welfare technology that could detect changes in their behaviour, and they reported no objections to a welfare technology that could identify their daily routine. In general, the participants conveyed that if the welfare technology improved their safety, it was good for them. One participant stated:

> When you feel that you have your five senses working, and you think that yes, I can live here for as long as I live, just knowing that I can live safe, be safe, knowing that I will be picked up if I fall, that is the most important. [P6]

The majority of the participants were familiar with other technologies and regularly used devices such as iPads, computers, e-mail, global positioning systems (GPS), smart watches, mobile telephones, Bluetooth, online bank transactions, and social media. Some participants also kept updated online medical journals that allowed healthcare personnel to review their medications and health concerns. One participant discussed welfare technology in the following terms:

Table 4 Subcategories, Categories, And Main Theme

Sub-Categories	Categories	Main Theme
i. Feeling confident- proactive approach to future technology	I. Preferences and concerns of welfare technology	Welfare technology - a valuable addition to tomorrow's homes
ii. Concerns and dilemmas		
i. Feeling healthy, independent, self-sufficient and safe	II. Reflections of today and tomorrow-awareness of own health	
ii. Facing own ageing- preparedness for unpredictable scenarios		

> Yes, I'm very interested in it [welfare technology] because I cannot think of moving out of my house … I also have thought about the possibility of installing electronics [devices in my house], just in case I fall, although I'm not that bad, I'm not there yet, but I can give my opinion [on welfare technology] anyways. [P5]

Most participants said that they had never fallen and that falling was not a concern for them; many said that they were not so old that falling would cause problems. For example, one woman stated:

> I have strong arms, so I can easily lift myself up [from the bathtub] and get out of it [P8].

However, most participants also said that they had changed their habits or bought assistive devices when they felt it necessary for their safety. For example, a few participants were afraid of falling in the shower, and one participant had called the central aid station and asked for safety rails to be installed in her shower; another participant had a small chair in the shower; several participants had replaced their bathtubs with shower stalls to reduce the risk of falling; and several stated that they kept a hallway light on at night to help avoid falls. Several participants had also changed their furniture to avoid falling and had removed carpets after tripping on them. Other participants mentioned using poles, boots with grips, or track spikes to walk on slippery ground because they did not wish to fall and break an arm or leg. One participant even said that he would like an apartment entirely adapted to his needs:

> I feel that, yes I have changed things, I have made it so it would be safer … [I would like] an apartment built so I can live there, with no door thresholds and an adapted bathroom, built so I can live there with a wheelchair or walker. [P4]

However, some participants noted that falling could happen to anybody, not only the older people, and that thus they did not worry about it much.

Regarding technological welfare adaptations, some participants had fall alarms and expressed that they had no need for additional welfare technology. However, others were glad to know about the existence of welfare technology that could assist them in the event of a fall. Furthermore, some participants were happy that welfare technology could provide peace of mind to their families and would avoid the need for their family to constantly check on them and worry if they failed to answer. For example, one woman mentioned that her relatives always feared the worst if she did not pick up the phone immediately when they called. Likewise, some participants wished for a waterproof fall alarm that could be used in the shower. Some participants were also open to the possibility of a wearable device, so long as it was small and comfortable, such as a watch or bracelet. Some participants also indicated a desire for an alarm with a GPS that could give an exact location to emergency services; most of the participants were more afraid of falling outside, for example while going for a walk, than of falling within their homes. One participant also expressed a desire for a GPS alarm in case they got lost:

> GPS could be good to have in case I begin to get Alzheimer's and I go for a walk and cannot find my way back, it [GPS] would be good. [P9]

Concerns And Dilemmas

Some participants also expressed concerns and dilemmas regarding the implementation of welfare technology. One participant also stated that she preferred to receive help from her family than from technology or healthcare workers. However, other concerns related to specific details about potential technologies.

One specific concern related to the costs of welfare technologies. All of the participants who owned fall alarms had purchased them with their own money, so that they would not feel like a burden on the municipality. Several said they would buy any device that could make their life easier and safer as long as they were affordable.

Participants also expressed concerns about a loss of autonomy and personal dignity from the use of welfare technology. They wondered who would control decisions about their technology use if they become weaker or developed a cognitive impairment, and they were concerned whether they would be forced to have a smart house; one man stated that

> I say that I do not want it [welfare technology] now, but at some point there will be someone who will say that I should have it without me even having a say on it. [P2]

However, he also reflected, with resignation, that if he developed dementia, his wishes would not matter in any case.

It was noteworthy that the majority of participants had no privacy concerns. Some said that they saw no inherent conflict between technology and privacy. One participant stated that

> No, privacy is not interesting for me, it is not important, there is nothing dangerous about it. [P8]

Others expressed that they were fine with sharing information with people who cared about them:

> I do not mind that the information about me is available to others who care about me [P4].

When asked with whom their private data should be shared, many said their doctors, while others said both their doctors and family members. Participants considered it practical for doctors to have their health data in case they needed assistance. Nevertheless, one participant did express concern about the misuse of her data:

> I am not afraid that people come and look at my health data information at the doctor, for example, I'm not afraid of that, there is nothing dangerous for me, but I think that it's bad if there would be misuse of my identity. [P7]

Likewise, another participant stated that they did not know how to protect their data.

Throughout the interviews, some participants expressed a concern that welfare technology could make them feel monitored; however, they still felt positive about it overall. Some said that the use of cameras would be inappropriate, but others thought that cameras would be acceptable if videos were only sent to their doctor in the event of a fall. Some participants also expressed a desire for welfare technology to be automated, as they felt that pressing buttons or programming a system would be tedious.

Participants also expressed concern about welfare workers losing their jobs to technology. However, one participant noted that technology always differed from generation to generation and that new changes needed to be embraced:

> … things can look quite obvious to a new generation, but then there are those barriers that must be broken for us [the older], we must accept that things don't stay the same. [P2]

Isolation was also mentioned as a concern. One participant stated that he did not wish to stay alone at home watching TV or staring at a wall unable to move if he became sick and had to rely on help. Instead, he regarded a nursing home as a place with people around:

> I saw when my wife was at the nursing home, there she had people to talk to. My neighbour has no one to talk to, I go every now and then [to visit her] for 10 or 15 minutes but, no, I will absolutely go to the nursing home, I already told my sons, if I begin to get dementia I don't want to stay at home and stare at the wall. [P3]

Most participants also stated that they preferred human care to technological care. However, some noted that they felt no need to bother home care staff for minor needs, such as pill administration; instead, they would prefer a pill-dispenser device. However, many emphasised that welfare technology should not replace human care, such as one woman who stressed that

> Nothing can replace human contact. The more helpless you are, the more you need for people to come and check on you once in a while. [P9]

Reflections Of Today And Tomorrow-Awareness Of Own Health

Feeling Healthy, Independent, Self-Sufficient And Safe

Most of the participants were autonomous and performed daily housework such as cooking, ironing, and grocery shopping. However, many said that they also hired cleaning aids, although mainly for convenience rather than out of necessity. In general, they took good care of their health and had an active life. Many had yearly medical check-ups, exercised several times a week, went for daily walks outside, or even tested their balance by standing on one leg.

All participants said that their independence, including the freedom to enjoy different hobbies and activities, was very important to them. They mentioned numerous activities, such as going to music clubs, hunting, watching TV, gardening, meeting friends for coffee, skiing, cooking, going to church and greeting people, going to dinner at social clubs, woodworking, knitting, reading, dancing, singing, etc. Some expressed that as long as they could live fully, they enjoyed their ageing. One of the oldest participants (89 years old) stated:

> I would like to live long, see how it goes with everything and everyone, as long as I can have fun, take part in things, see, read, and dance and sing … I would very much like to be independent and live by myself. [P9]

An interesting finding was that many participants expressed no fear of dying, but were afraid of falling or of being mistreated, hospitalised, or in pain. One participant noted:

> I have lived a long life already, and I cannot think of being crippled and unable to move or the like, lying in a bed or the like, no. [P5]

Regarding their situational safety, all participants felt safe in their neighbourhoods and stated that neighbours took care of each other; for example, neighbours called to check on them if they saw something off, and vice versa. One said:

> I was in [city name] last week and stayed overnight but I didn't turn off the lights from my house when I left, because I didn't want my house to be so dark when I came back. So she [neighbour] called me in the evening and asked me if I was sick because she saw light in my house but no noise. [P6]

Similarly, some participants knew a neighbour's phone number and had given a relative's phone number to a neighbour to use in case of emergency. In addition, one participant's neighbours had a key to her house to use in case something happened to her. Others said that they always told their neighbours if they planned to be away for a night or longer.

Facing Own Ageing- Preparedness For Unpredictable Scenarios

Although all participants felt relatively healthy, most had minor health problems, such as back pain, vertigo, high blood pressure, sciatica, heart problems, or knee pain. Most of the participants expressed that their health conditions determined their life choices and activities; sometimes they had needed to stop an activity or change their habits due to ageing, such as needing to sleep at specific times due to back pain, giving up playing golf due to increasing allergies, reading less, or playing cards instead of doing more physical activities.

Participants were also aware of the increased risks of becoming sick due to ageing. All but one were widowed and had experienced the loss of a partner, and several of the male participants expressed that it had been difficult to deal with their wives' sicknesses. In addition, some participants had neighbours with health issues, which had caused them to reflect about their own health risks. Participants mentioned strokes, being confined to a wheelchair, falling and being unable to get up, and needing assistance with medication as being among their fears of future health problems. Most of the participants had prepared an action plan to implement in case something happened to them, such as calling an ambulance immediately. Most also said that they would prefer that any welfare technology alarm be sent directly to an ambulance first, and then alert their families afterwards.

Some participants also noted that living alone could present risks and challenges, especially in case of sickness. Some of the male participants also expressed a dislike of living alone:

> I think it is very sad to sit here alone in the mornings, when it is dark and I don't want to go out … you come home, there is no one waiting for you, no, nothing, I have done it for several years now. [P3]

However, many of the female participants enjoyed living alone. One woman said:

> It is a luxury you know, it's a luxury to live like this, alone all the time, I eat whatever I want, I can buy whatever I want, eat food whenever I want, and I enjoy myself with it, I can go to bed whenever I want (laughs), I can watch whatever I please on the TV, and I do not need to consider anybody, but of course, one misses one or two to talk to, on what I have seen on the TV, on what I have read. [P9]

These two participants gave different perspective of living alone. Most interestingly, the five female participant shared the same perspective of enjoyment living alone, while the four male participants expressed displeasure of living alone.

Reflecting on the question of staying in their homes for the rest of their lives, one woman expressed that the future is uncertain:

> That is hard to answer because it is hard to say what one wishes for, one can relate to how the reality is today, there's no problem to live here, but no one knows the future, so I cannot answer that exactly, it will be what it will be … But I don't go around worrying about how my future will be, I don't do that. [P7]

Welfare Technology—A Valuable Addition To Tomorrow's Homes

Participants in this study described their attitudes towards welfare technology based on their current experiences. They reflected on the benefits and drawbacks that welfare technology could bring as they aged. Most desired to live in their homes for as long as they could maintain their independence and a dignified lifestyle, suggesting that welfare technology could be a valuable addition for them in the future. The main theme we identified regarding our participants' attitudes towards welfare technology can therefore be summarised as 'welfare technology—a valuable addition to tomorrow's homes'.

Discussion

This study explored the attitudes of older people towards welfare technology. Throughout the interviews, participants reflected about their current and future lives. Overall, most of the participants felt themselves to be healthy and independent, but they were aware of their ageing and had reflected on changes that might be needed in the future to make it safer to remain in their own homes. Most participants tried to maintain a healthy lifestyle, both physically and mentally; they stated that health was the most important factor for ageing in place and that their lifestyle was dictated by their health. They were therefore aware that ageing is accompanied by frailty and vulnerability, especially when living alone, and they recognised the need to adapt as they aged and were open to making changes as needed. This likely influenced their receptiveness to welfare technology. In addition, some participants had already adapted their homes to their needs by removing furniture or carpets to reduce the risk of falling, and many were therefore glad to learn about the development of HBM welfare technology.

Notably, all participants stated that they trusted the Norwegian healthcare system. Most said that health alarms should first be sent to their doctors and only second to their families. One possible reason for such trust could be that Norway, along with other Scandinavian countries, operates a 'welfare state' that emphasises egalitarianism and individual autonomy regardless of social class.[5] Scandinavians therefore believe in freedom with autonomy[5] and the right to good public services. A similar context to the Scandinavian is the one of the United Kingdom, where both regions have a single-payer health care system which facilitates the government willingness to invest and engage in welfare technology promotion in public policy. These countries provide good support for the transition to welfare technology, partially thanks to the government implementation of privacy policies and regulations, contrary to the context of the United States.[50] In addition, the healthcare provided by the Norwegian government is regarded as a ‘material basis for not becoming dependent on others’[5] including one’s family. According to the Norwegian Municipal Health and Care Service Act of 2011, municipalities in Norway are obligated to provide healthcare to residents when needed.[51] However, although all of our participants were aware of the municipalities’ legal obligations, they stated that they preferred to buy anything they could afford instead of asking for health care services to the municipality for small needs, such as pill administration. Several participants also viewed welfare technology as advantageous because they perceived it as being more cost-effective than human healthcare services, as also reported in previous studies.[25]

Most participants also said that they did not wish to be a burden on their families or society. This sense of 'burden' might be due to the fact that families in Norway, as in other Scandinavian countries, are seen as having a 'balance reciprocity between the social and emotional obligations with individual boundaries and autonomy'.[5] As such, traditional obligations are disregarded because personal dependency is reduced. Thus, there is no obligation for children to take care of their parents when ageing, nor do ageing parents expect it. This could be seen in some participants’ references to fears of losing their autonomy and independence if they moved in with their children.

Another interesting finding was that the majority of the participants frequently used technology, contrary to a common belief that older people are reluctant to engage with technology.[52] Previous studies have also found that older people’s perceptions of technology depend on their 'personal, social, and physical context'.[53] In this study, the participants embraced technology that made their lives easier, such as online banking and keeping in touch with their families via social media. Thus, most participants also felt positively about welfare technology, which they regarded as enabling their safety while preserving their autonomy.

In contrast, some participants were not worried about falling and said that they currently had no ageing-related difficulties; they stated that they felt young and healthy and did not need help. However, they acknowledged that maybe 'other older people' might need it or that they might even need it themselves in the future; some noted that the future is uncertain and some things are beyond individual control. Consequently, many participants said that they had no need for welfare technology at present but acknowledged that this could change in the future, indicating an overall positive response to the development of welfare technology.

Another important finding was participants’ preferences regarding the use of technology versus human care. In general, participants preferred the idea of a combination of both. They felt that welfare technology could better preserve their independence and accommodate their preferences, and welfare technology was therefore preferable to moving to a nursing home as long as they could still take care of themselves. A possible reason for this preference among the participants could be that Scandinavian countries are recognized to be early adopters of technology for health care usage.[54] However, a nursing home environment was preferable if they needed constant care or were no longer self-sufficient. This finding is consistent with previous research that human care and attention cannot be replaced with technology, because technology cannot handle human emotions or unexpected interactions.[19,55] Previous research has also found that increased technology use can lead to patients being neglected;[56] with technology providing care and 24 hr monitoring, 'face-to-face contact and hands-on care'[57] can decrease, and the consequent increase in social isolation is detrimental to older people's social well-being.[8,58] Consistent with these findings, participants in the present study emphasised that they did not wish to be isolated and that technology should never replace humans.

Although gender perspective were kept in mind during this study, only minor difference were found and should be used carefully due to the small number of participants. The sample consisted of almost half women and half men. The female participants expressed satisfaction in living along while the male participants were more social driven, and disliked to be alone.

Losses of dignity and autonomy were also central concerns among the participants. Ageing in place claims to be more cost-effective than nursing home care,[25] but many participants therefore wondered if their dignity would be sacrificed to the economic interests of the municipality, such as by being forced to use welfare technology if they became cognitively impaired. A similar tension can be seen between the values of autonomy and safety.[19] For example, Jacobs, et al[19] argued that the use of technology in healthcare can be simultaneously both humanising and dehumanising, and they emphasised the importance of considering different aspects of person-centredness when implementing such technologies. Surprisingly, however, the participants had no concerns about privacy; instead, they felt that their safety was paramount. Hence, any concerns about being monitored or other invasions of privacy were superseded by concerns about safety. This is consistent with previous findings that older people are willing to trade privacy for autonomy[8,50] and that the need for welfare technology thus outweighs privacy concerns.[20]

Strengths And Limitations

A strengths is that, although this study was performed in a Norwegian context, we consider the findings to be relevant in other contexts in which publicly funded healthcare for older people is regarded as a right and a form of natural autonomy.[5]

Another strength of this study is its focus on older women and men representing a group sparingly studied. The study thus contributes a new understanding of this group's attitudes towards welfare technology. However, this study was exploratory in nature and our participants did not have personal experience of HBM welfare technology; further research is therefore needed about older people's preferences and concerns after having "real" experiences with HBM welfare technology in their homes.

The participants all shared many things in common, such as self-perceived good health, an active lifestyle, and frequent use of modern technology; this represents a limitation of our sampling strategy that may have biased our results. It is conceivable that regional differences could also influence older people's attitudes to welfare technology. For example, people from other parts of the country might have contributed to different attitudes. However, although a larger and more heterogeneous sample could lead to a more in-depth understanding, our participants nonetheless offered rich and varied descriptions of critically relevant issues.

Research on the implementation of welfare technology in older people is limited and this study contributes to the knowledge on this topic. Further research should pay attention to gender perspective differences, older people who are already users of welfare technology services, more attention to the different dimensions of participant's health, multiple ethnicities, or a more varied grouped of socio economic status. Further research should also include younger older people (60–75 years old) than those targeted by the present research. This population might have different concerns regarding the use of such technology, including greater concerns related to privacy, as compared to the participants (> 75 years old) interviewed in this research. Their views are important as they may still be among the first group with a widespread ability to implement welfare technology.

Conclusion

The use of welfare technology is growing and promises many advantages for older people. HBM welfare technology that can detect abnormal behaviour in an individual, such as falls, is in the early stage of development, and older peoples' attitudes towards its use therefore need to be explored. The present study suggests that older people view welfare technology as very convenient. The participants in this study were not 'afraid' of technology; rather, they perceived it as empowering, and welcomed any type of help to make their life better, easier, and safer. They wished to maintain their independence and to live at their own home for as long as they were self-sufficient, and although they raised some concerns and dilemmas about welfare technology, these were less important to them than the possible improvements to their safety and ability to age in place.

Abbreviations

HBM, Human behaviour modelling; GPS, Global positioning system.

Acknowledgments

We thank all interviewees for participating in this project. We would also like to thank the SMART research group at University of South-eastern Norway for their financial support with interview transcriptions. The contribution did not have any role in the planning nor carrying out the study.

Disclosure

The authors report no conflicts of interest in this work.

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Conference Article 1

A Discrete Event Oriented Framework for a Smart House Behavior Monitor System

Pfeiffer, Carlos F., Veralia Gabriela Sánchez, and Nils-Olav Skeie

12th International Conference on Intelligent Environments (IE). IEEE, 2016

DOI: 10.1109/IE.2016.26

Conference Article 2

Decision Trees for Human Activity Recognition in Smart House Environments

Sánchez, Veralia Gabriela, Nils-Olav Skeie

Proceedings of The 59th Conference on Simulation and Modelling (SIMS 59), 26-28 September 2018, Oslo Metropolitan University, Norway, Issue 153, 2018-11-19, Pages 222-229, ISSN 1650-3740

DOI: 10.3384/ecp18153222

Decision Trees for Human Activity Recognition Modelling in Smart House Environments

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Abstract

Human activity recognition in smart house environments is the task of automatic recognition of physical activities of a person to build a safe environment for older adults or any person in their daily life. The aim of this work is to develop a model that can recognize abnormal activities for assisting people living alone in a smart house environment. The idea is based on the assumption that people tend to follow a specific pattern of activities in their daily life. An open source database is used to train the decision trees classifier algorithm. Training and testing of the algorithm is performed using MATLAB. The results show an accuracy rate of 88.02% in the activity detection task.

Keywords: *intelligent environment, behaviour modelling, pattern recognition, probabilistic model, predictive model, Norway*

1 Introduction

Human activity recognition modelling (HAM) in smart environments is an important area of research. Smart houses are being developed to improve and ease the life of the inhabitant. The idea of implementing HAM is to recognize the activities of a person in order to adapt the house to its user (Reaz, 2013; Vainio et al., 2008).

A smart house is defined as any living environment that has been carefully designed to support its inhabitant in carrying out daily activities, as well as to promote independent lifestyles (Chan et al., 2008).

People tend to follow a pattern in their daily live (Alam et al., 2010; Bourobou and Yoo, 2015). Therefore, it is possible to recognize the activities of daily life (ADL) a user performs, such as eating, toileting, bathing, dressing, etc. This recognition task is also known as human activity recognition (HAR).

Once the ADL recognition task is done, HAM can use the output from it to learn the pattern of the user and model the user's activities. The modelling has the potential to detect any deviation from the usual pattern.

Detecting abnormal activities has several applications including assisting older adults. In Norway, 38.5% of households with people aged 65 and over are living alone (sentralbyraa, 2018). Hence, a smart house can help the older adult to remain living in their own home for as long as possible (Sanchez et al., 2017).

In this work, HAR is implemented using an open source database. The output of the HAR is used for the HAM. HAM generally refers to the task of modelling the person activity pattern together with time. Therefore, accurate activity recognition is a crucial part for good HAM.

Decision trees are used to develop the HAM. Decision trees are a probabilistic algorithm that is able to predict the next step or value by learning from data. An open dataset is used for training the model.

2 Related Work

Decision tree is a supervised learning method. This method has been used for several tasks in the field of pattern recognition and machine learning as a predictive model. The main goal is to predict the next value given several input variable.

Previous studies on pervasive environment using decision trees have been successfully implemented (McBurney et al., 2008).

In smart house environments, an 80% accuracy was achieved using decision trees on 20 everyday activities in a research by Bao and Intille (2004). Another research based on decision tree with good result for ADL is the work by Fan et al. (2014).

3 Design and Methods

Figure 1 shows the methodology flow in this work.

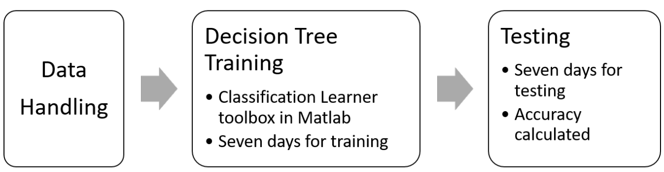


Figure 1. Methods

3.1 Decision trees

Decision trees is a hierarchical model also known as classification and regression trees. They have the property of predicting response from data.

The attributes of the decision trees are mapped into nodes. The edges of the tree represent the possible output values. Each branch of the tree represents a classification rule, from the root to the leaf node (Lara and Labrador, 2013).

3.2 Software

MATLAB is used in this study for developing the model. The classification learner toolbox was specifically used for training the tree. The code from the classification learner toolbox was exported and saved for later use with any other dataset. Testing was also coded in MATLAB.

Finally, the program Wolfram Mathematica is used for the results plots presented in this article.

3.3 Dataset

An open dataset is used in this study. The dataset has been previously used in other research and is known in the HAR field (Ordónez et al., 2013). The dataset is named "Activities of Daily Living (ADLs) Recognition Using Binary Sensors Data Set" and is available for download at (Ordonez, 2013). The purpose of using an open dataset is to obtain unbiased results.

The dataset consists of annotated ADLs collected by two different users living on a daily basis in a smart house. The activities in the dataset were manually labelled by the users. Table. 1 presents the dataset attributes.

Table 1. ADLs Database

Name	*Value*
Setting	Apartment
Number of Rooms	4 Rooms + Hall/Entrance
Number of labelled days	14 days
Labels (ADLs included)	Leaving, Toileting, Showering, Sleeping, Breakfast, Lunch, Dinner, Snack, Spare Time/TV, Grooming
Number of sensors	12 sensors
Sensors	PIR: Shower, Basin, Cooktop Magnetic: Maindoor, Fridge, Cabinet, Cupboard Flush: Toilet Pressure: Seat, Bed Electric: Microwave, Toaster

Two instances of data exist corresponding to each user living in the smart house. One dataset of 14 days (OrdonezA), and the second dataset of 21 days (OrdonezB). The first dataset data is depicted in Fig. 2. The first dataset is used this work for creating and testing the model. The second dataset (OrdonezB) is implemented later in order to test the model with a different dataset.

3.3.1 Data Handling

The variables used from the dataset are "Date", "Time", "Activity", and "Room". Another variable named "position" was added to improve the recognition task. This variable *position* correspond to one of the three following values: *laying, sitting, standing*.

Table 2 depicts the first day from the dataset. The dataset is in a text file format.

Table 2. Day 1 example of the dataset

Date	*StartTime*	*EndTime*	*Activity*	*Room*
28-11-11	02:27:59	10:18:11	Sleeping	Bedroom
28-11-11	10:21:24	10:23:36	Toileting	Bathroom
28-11-11	10:25:44	10:33:00	Showering	Bathroom
28-11-11	10:34:23	10:43:00	Breakfast	Kitchen
28-11-11	10:49:48	10:51:13	Grooming	Bathroom
28-11-11	10:51:41	13:05:07	Spare Time	Livingroom
28-11-11	13:06:04	13:06:31	Toileting	Bathroom
28-11-11	13:09:31	13:29:09	Leaving	Hall
28-11-11	13:38:40	14:21:40	Spare Time	Livingroom
28-11-11	14:22:38	14:27:07	Toileting	Bathroom
28-11-11	14:27:11	15:04:00	Lunch	Kitchen
28-11-11	15:04:59	15:06:29	Grooming	Bathroom
28-11-11	15:07:01	20:20:00	Spare Time	Livingroom
28-11-11	20:20:55	20:20:59	Snack	Kitchen
28-11-11	20:21:15	02:06:00	Spare Time	Livingroom

In order to model the decision tree, a sample was drawn from the dataset. All the 14 days in the dataset were stopped when the activity *leaving* was found. Seven days were used for training and seven days were used for testing.

The dataset text values were coded to numbers in order to develop the MATLAB code. Table 3 shows the *rooms* with their respective codes.

Table 3. House tooms and their code

Name of Room	*Number Assigned*
Bedroom	1
Bathroom	2
Kitchen	3
Livingroom	4
Hall	5

Numbers were also assigned to the *activities* to make the learning and decoding process more feasible. Table 4 shows the *activities* with the assigned codes.

Table 5 shows the coding used for the *position* values.

A total of 9 *activities*, 5 *rooms*, and 3 *positions* are used.

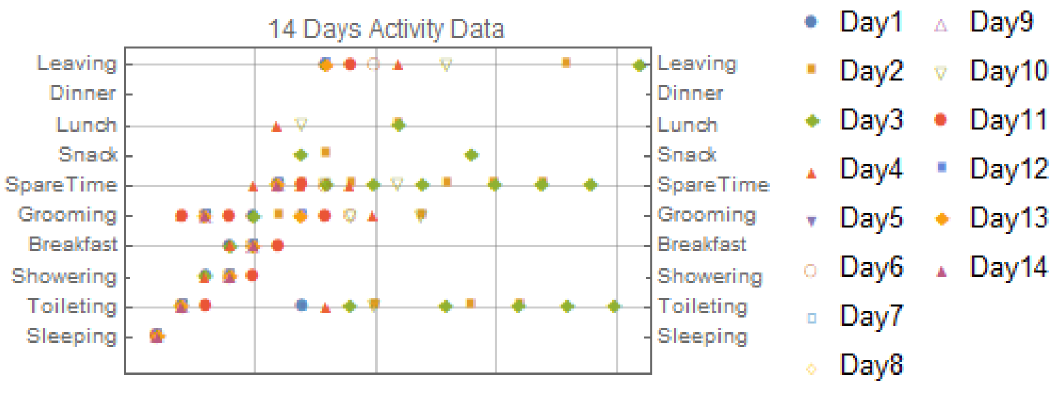


Figure 2. Activities Dataset Graph

Table 4. Activities numbers and their code

Name of Activity	*Number Assigned*
Sleeping	1
Toileting	2
Showering	3
Breakfast	4
Grooming	5
Spare time/TV	6
Snack	7
Lunch	8
Leaving	9

Table 5. Position numbers and their code

Name of Activity	*Number Assigned*
Lying	1
Sitting	2
Standing	3

3.4 HAR Modelling (HAM)

HAM refers to the modelling of the behaviour or activity of the person. Behaviour is regarded as an activity with duration, i.e, the time elapsed from start to end of an activity and time of day (Pfeiffer et al., 2016). For example, a behaviour can be having breakfast, which consist of opening the refrigerator, cooking, sitting and eating breakfast. This set of activities are given in a time span (time elapsed from start to end), and usually in the morning (time of day).

Normal and abnormal activity and behaviour can be detected in a smart house by analysing both, the activity and the time. Abnormal activity detection main purpose is to warn a member of the family or caretaker whether something is wrong with the person. This can be regarded as anomaly. "Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behavior" (Chandola et al., 2009).

4 Experiments

The dataset used in this study is available in a text file only. Therefore, the dataset was exported to an excel file. The dataset contains 14 days of data in total. Two files were created, one for training and one for testing. Random numbers was generated in MATLAB with the *randperm* function to randomly select seven days for training. The numbers selected according to the random generator were days: 12, 10, 5, 14, 1, 7, and 6. Hence, these days were use for training. The remaining days (2, 3, 4, 8, 9, 11, 13) were used for testing.

A new variable called *duration* was added. The variable *duration* was calculated using the *time* data from the dataset and consist of the time spent in each activity, from start to end of each activity. The *duration* value was calculated in seconds.

In the excel file, the text values of the dataset were coded to numbers. The variables *room, position* and *activities* were coded as explained in section 3.3.1. The *room* values were coded to numbers from 1 to 5. The *position* values coded to numbers from 1 to 3. The *activity* values were coded to numbers from 1 to 9.

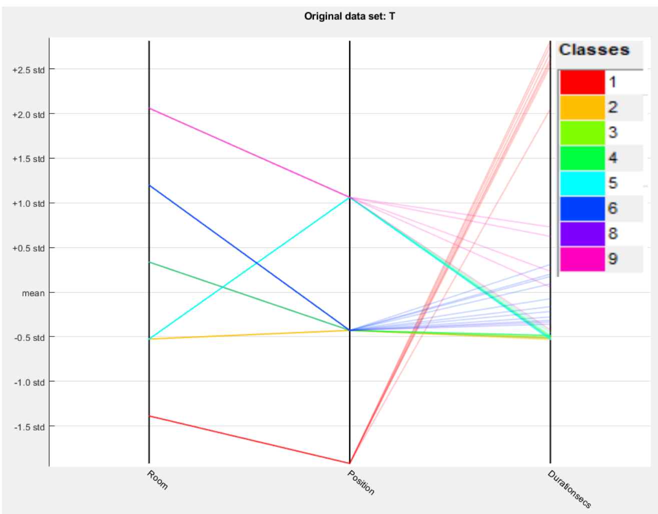


Figure 3. Parallel coordinated plots

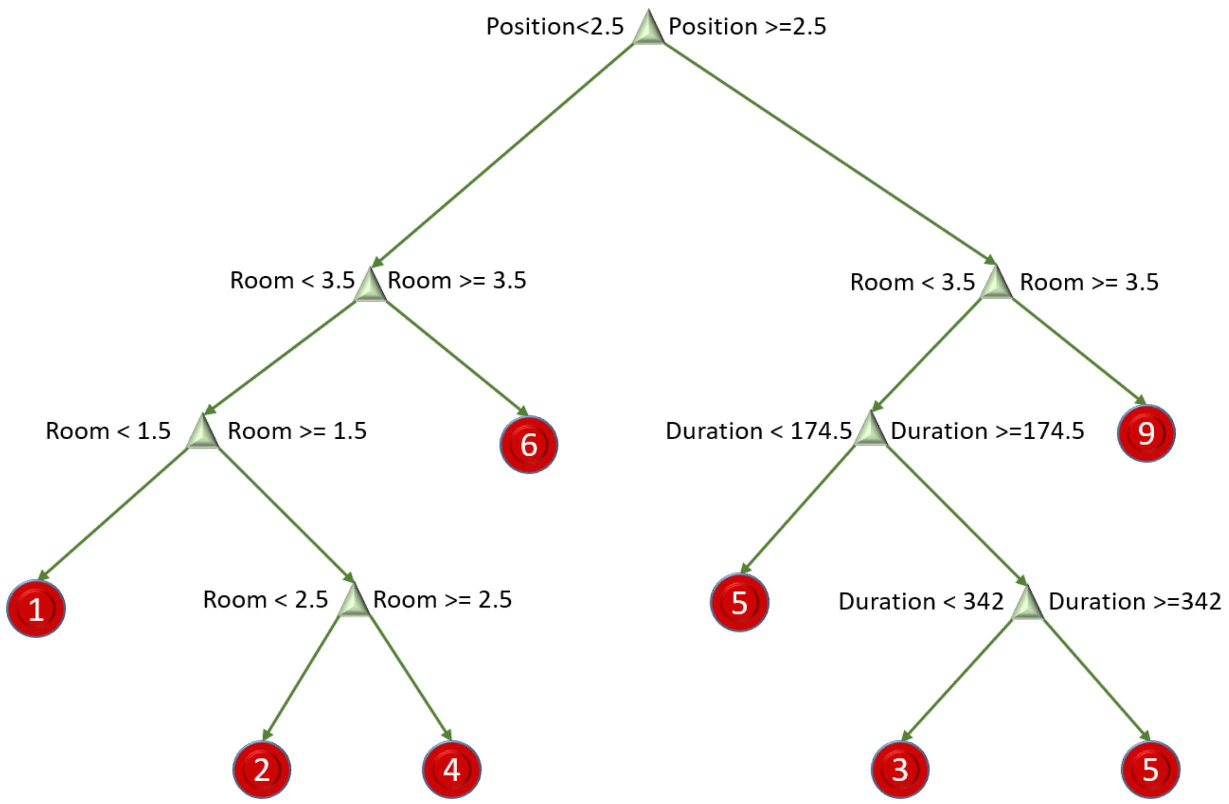


Figure 4. Trained Decision Tree. Red circles represent the activities

Both excel files were imported to MATLAB as table data type. The training was performed using the integrated classification learner toolbox. The variables used for training the decision trees are the *room*, *position*, and *duration*. The output variable is the *activity* data.

Figure 3 shows the parallel coordinated plots of the data. The variables *room, position*, and *duration* are plotted to show the relationship between them. According to Figure 3 , it is possible to see that activities 3 and 5 (*showering and grooming*) follow almost the same path line in the graph. Also, activities 4, and 8 (*breakfast and lunch*) almost follow the same path line, with the *duration* barely different for each of the two activities. Activity 7, *snack*, was not found in the training dataset.

Once the tree is trained, testing is performed with the remaining seven days of the dataset: days 2, 3, 4, 8, 9, 11, 13. The testing consists on using the variables *room*, *position*, and *duration* as input data. The response or output is the *activity* value. Each day from the testing dataset was tested and compared to the real data.

A new fictional test set was created in order to test the model with abnormal data, as showed in table 6. The test set consists of a fictional single day. The table shows that the *duration* of some of the activities were exaggerated. In addition, the *position: lying* of the first activity in the *hall* room should qualify as abnormal behaviour.

Result plots were obtained using the Mathematica software. The actual data and the predicted data for each of the testing days was copied to Mathematica and plots were coded to visually present the results.

Table 6. Added test day

Room	*Position*	*Durationsecs*	*Activity*
Hall	Lying	10000	-
Bathroom	Sitting	15000	toileting
Bathroom	Standing	450	grooming
Living-room	Sitting	9000	spare time
Living-room	Sitting	9500	spare time
Hall	Standing	412	leaving

Finally, the total computational time was measured.

5 Results

Figure 4 shows the trained decision tree. The decision tree model was able to classify seven out of nine activities in the dataset.

Figure 5 shows the number of observations for each of the activities. The true class is in the y-axis and the predicted class is in the x-axis. It is possible to see that there are no observation in the training dataset for activity number seven (*snack*), and only one observation for activity number eight (*lunch*).

Most error counts in figure 5 occurred in activities that are performed in the same *room*, such as *showering* and *grooming* (3 and 5). However, this number of observations

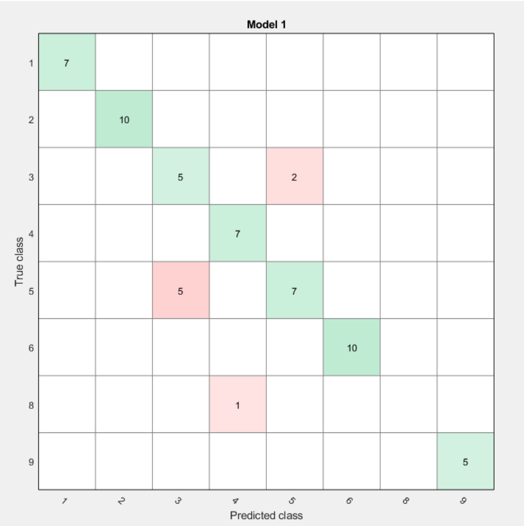


Figure 5. Number of observations

with errors is low.

Figure 6 shows in percentage of success and errors prediction in the training data, called "positive predictive values false discovery rate". The highest false discovery is 50% in the activity *grooming (5)*. The model classified the activities *showering (3)* half of the times instead of the true class *grooming (5)*.

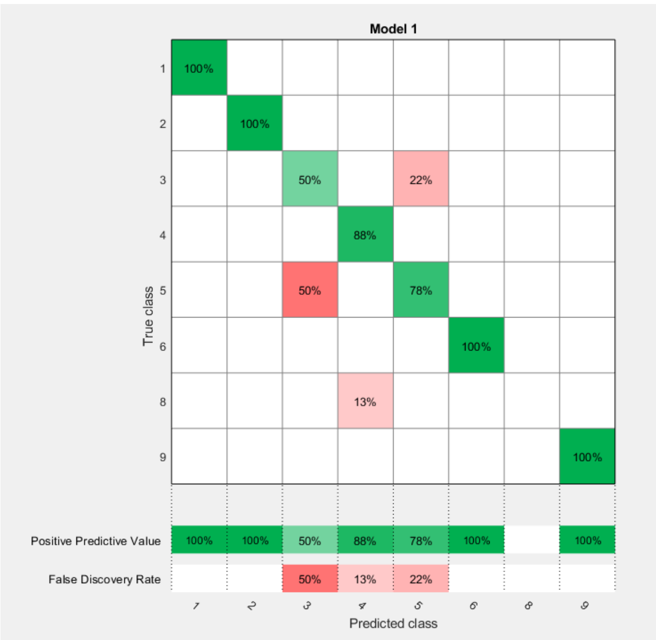


Figure 6. Positive predictive values and false discovery rates

For the activity *grooming (5)*, the model had a false discovery rate of 22%, classifying the activity *showering (3)* instead of *grooming (5)*.

For the activity *lunch (8)*, the model classified the activity *breakfast (4)* with a false discovery of 13% .

Figure 7 shows the results of the test. Days 2, 3, 4, 8, 9, 11, and 13 were used for testing. Some prediction errors were found when comparing the actual data with the estimated data.

Most of the errors were found between the *grooming* and *showering* activity, and between the *breakfast* and *snack* activities. A possible explanation for these prediction errors is that both of these activities are performed in the same room, *bathroom* and *kitchen*, respectively.

Figure 7h shows the results of the added fictional day with abnormal behaviour data. The model predicted the activity *Spare Time* instead of finding an abnormal behaviour in the first activity. The true positive-false positive rate for each fo the predicted activities are shown in table 7.

Table 7. True positive \false positive rate for each activity

Activity	*True Positive*	*False Positive*
Sleeping	100%	0
Toileting	100 %	0
Showering	77%	23%
Breakfast	98%	2%
Grooming	94%	6%
Spare time	100 %	0
Lunch	36%	64%
Leaving	100 %	0

Finally, the total accuracy of the activity recognition task is 88.02%. The computational time of the model, consisting of training and testing is around 3 seconds.

5.1 Test on second dataset

The model was tested on the second dataset (OrdonezB) consisting of 21 days, also open source as described in section 3.3. The purpose of this second test is to verify that the model works with any dataset.

In this test, the entire dataset was used, without sampling. The dataset was also processed as described in section 4. The values were coded to numbers. A total of 10 *activities*, 5 *rooms* and 3 *positions* were used.

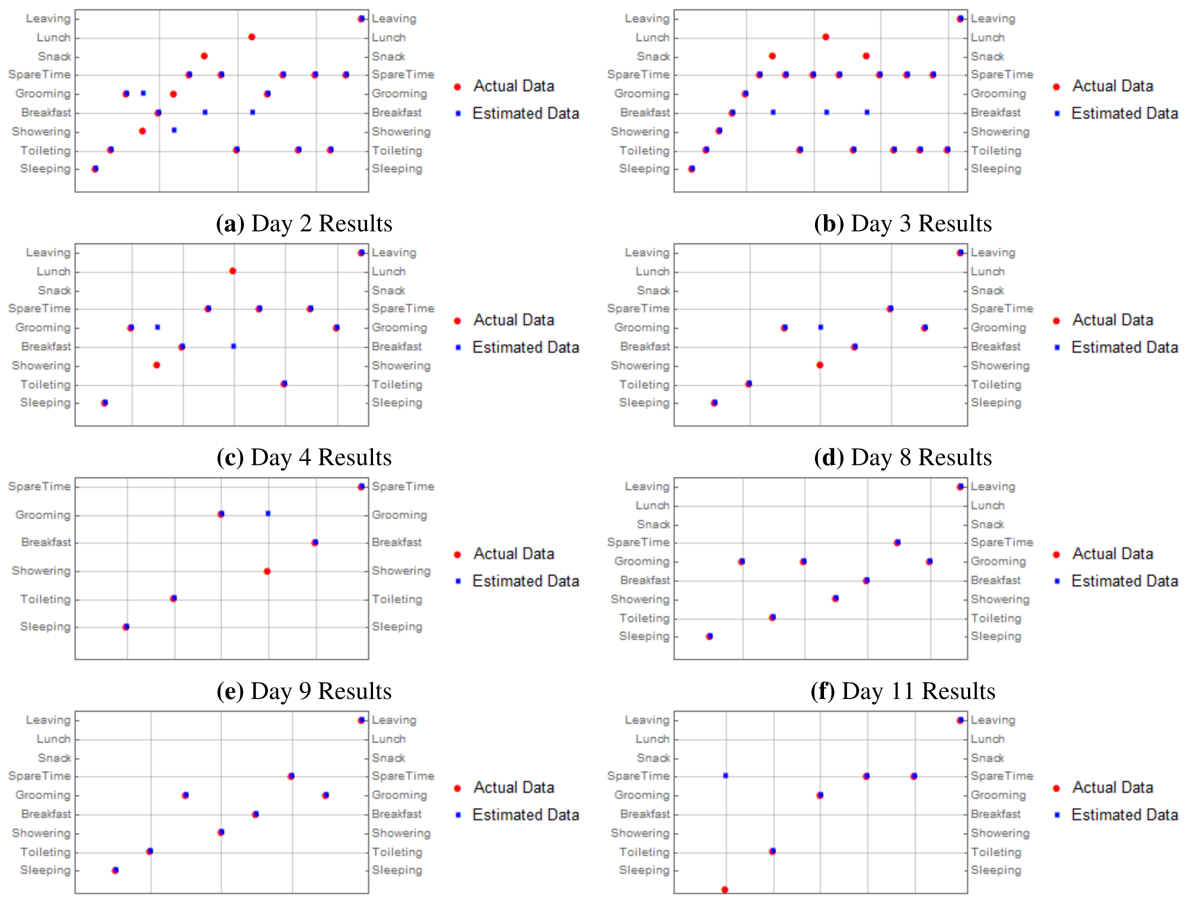
The results showed that the model worked as well as in the experimental work (dataset Ordonez A). Like in the experimental work, minor mistakes were found in the prediction task corresponding to activities made in the same room. Namely *bathroom* and *kitchen*. Therefore, the model presented here is able to work with any dataset.

6 Discussion

In this work, decision trees are researched to perform human activity recognition modelling.

The decision tree classified seven out of nine activities. This is because there are no observation of activity *snack*, and only one observation for activity *lunch* in the training dataset. Therefore, the model could only classify seven activities in total.

Some predictions presented minor error rates. One possible reason for the these error rates is that there are *rooms*



(a) Day 2 Results

(b) Day 3 Results

(c) Day 4 Results

(d) Day 8 Results

(e) Day 9 Results

(f) Day 11 Results

(g) Day 13 Results

(h) Added fictional day results

Figure 7. Results

that allow different types of activities. Hence, the recognition task is more difficult. For example, in the room *bathroom*, three different activities are performed: *showering, toileting and grooming*. Thus, the model tends to predict the highest probability of the *activity* given the room *bathroom*.

This is the same case for the room *kitchen*, where activities *breakfast, lunch and snack* are performed. The activity *lunch* has an error rate of 64%. From figure 5 it is possible to see that there is only one observation of the activity *lunch*. Therefore, the model would hardly predict this activity. Instead, the model predicts the activity *breakfast*, because it has the highest probability.

Decision trees are probabilistic algorithm and thus produces some errors in the prediction task. As any probabilistic algorithm, decision trees will always chose the highest probability according to the trained data.

In general, the finding suggest that decision trees are a good tool for HAR with 88.02% accuracy. However, for the HAM, the model does not detects abnormal behaviour as well as it does HAR. When a fictional single day test set was created to check the performance on an abnormal day, the model did not meet the expectations in the anomaly detection task.

The most like reason for this, is that decision trees does not always enforce to check every variable before estimating a results. Consequently, in the added fictional test day with room *hall* and position *lying*, the tree predicted the activity *spare time*. Thus, the tree does not check for the other variables of *room*, nor *duration*. The model should have detected an abnormal behaviour in this scenario, since *lying* in the *hall* is not a normal activity, but a possible fall.

Another reason for the model not detecting abnormal behaviour is that abnormal situations need to be trained in decision trees. This means that all possible abnormal scenarios need to be learned *a priori*. As a result, the finding suggest that decision trees are not the best option for detecting abnormal activities or behaviour.

The model was also tested with the second dataset available (OrdonezB) to verify that the model is able to work with any dataset. The results obtained were similar to the experimental work. Minor mistakes were found in activities performed in the same room.

Possible solutions for improving the model are more research on how to enforce the decision trees to check every single parameter. Another option could be to combine decision trees with another probabilistic method to increase the accuracy of the model.

Finally, HAM would ideally keep the activity history of the user in order to model the behaviour of the person. For example, if the user has followed the pattern *wake up, toileting, grooming, showering and breakfast*, the most normal behaviour would be not to repeat any of those activities again within a given frame time.

7 Ethics in Smart Houses

Smart house technology, like any other type of technology, can carry many ethical challenges. Therefore, a separate study has been carried at USN to address this topic. We consider that the ethical aspects are an important part of our research in smart house technology.

Among the main challenges found that smart houses presents are cost-effectiveness, privacy, autonomy, informed consent, dignity, safety, and trust (Sánchez et al., 2017).

These challenges are central to keep in mind when developing a smart house system. Developers need to be aware of these challenges in order to provide a safer and dignified environment for the users. Nevertheless, it is important to acknowledge that smart house systems, at some point, cannot solve all the problems that are related to ageing, disabilities and diseases. There are needs that people develop as they age and smart house technology cannot help them any more (Sánchez et al., 2017).

8 Conclusion and Future work

In this study, activity recognition modelling (HAM) is researched. The goal is to find the normal and abnormal behaviour of the person living in a smart house. Decision trees have been used to perform activity recognition because they can predict responses to data. The output from the activity recognition task is used as an input for the modelling task.

The input data for the decision trees learning task are the *rooms, duration* and *position*. The responses are the *activities*. A total accuracy of 88.02% was achieve for activity recognition using decision trees. Thus, decision trees can be a good tool for activity recognition. However, HAM did not meet the expected results.

The reason for this is that decision trees does not enforces to verify every single input variable before calculating a result. Therefore, more research on how to check every variable before estimating a results needs to be studied. Alternatively, combining decision tree algorithm with another probabilistic model could be a possible solution for HAM.

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Conference Article 3

Legal Aspects on Smart House Welfare Technology for Older People in Norway

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12th International Conference on Intelligent Environments (Workshops). 2016

DOI: 10.3233/978-1-61499-690-3-125

Intelligent Environments 2016
P. Novais and S. Konomi (Eds.)

doi:10.3233/978-1-61499-690-3-125

Legal Aspects on Smart House Welfare Technology for Older People in Norway

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Abstract.
A Smart House Welfare Technology project to facilitate the independent living of older people at their home is being developed at the University College of Southeast Norway (USN). Smart Houses are a promising and cost-effective option of improving access to home care for older people. The project models behavior patterns using sensor information, detects when deviations of these patterns occur, and notify caretakers in case of a potential dangerous situation. In order to implement the project, it is necessary to consider the legal areas related to Smart Houses development. Therefore, the purpose of this article is to describe existing legal aspects on the deployment of Smart Houses for older people, with emphasis on Norway. The main legal aspects identified were data privacy, data access and management, stakeholders interests , and informed consent.

Keywords., Legal issues, data privacy, informed consent, Scandinavia, elderly

1. Introduction

The main goal of the "Smart House Welfare Technology" (SHWT) project at the University College of Southeast Norway (USN) is to provide the user with the opportunity to live independently at their own home for as long as they are able to, with a dignified independent lifestyle. In Norway, as of January 2016, the population aged 67-79 years represented 10.1% of the total population, and the oldest, 80 years and over represented 4.2% [1]. The ratio of persons aged 67 and over to those aged 20-66 has increased 31.9% from 2005 to 2015. Furthermore, this trend will continue to increase over the years, and by 2060, the group 67 and over will increase to around 19% [1].

The SHWT system seems to be cost effective. In Norway, the majority of older people prefer to live at their own home for as long as possible. The average cost of home health services provided by the municipality of Norway is approximately NOK 227 000 per year per person, while the cost of a person living in a nursing home is estimated to NOK 900 000 per year, as of 2013 [2,3]. Home health services provided

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by the Norwegian government include nurses visiting the older person at their home and assisting them. However, these analyses show that it can still be more cost-effective to allow people live at their homes [4] for as long as they are able to, if their safety is not compromised.

Given the importance of the Smart House project and that the targeted group is conformed by older adults, it is essential to study the legal aspects on how the project will affect the user and the population in general. In this article, description of the main legal concerns that Smart Houses technology present will be disclosed.

2. Methods

The aim of this article is to assess the legal aspects that arise when implementing Smart House systems for older people in Norway. Two search processes were performed: bibliographic search and laws search.

2.1. Bibliographic Search

The search process consisted of a manual search for relevant articles from the year 2000 to the year 2016. All papers containing the terms "legal", "Smart House" or "Smart Home", "elderly" or "older", and "Norway" as main subject headings, abstract, and/or keyword were identified.

The papers included in this article were selected because they met the criteria of either empirical studies or literature surveys on the legal aspects related to welfare technology. In addition, the journals chosen were sources for other literature reviews on Smart House systems. The search was restricted to English written documents.

2.2. Laws search

In addition to the bibliographic search, the law and the Health Ministry regulations from Norway were searched, as well as a search on the European Union law. No restrictions on the language of the documents were made for this.

2.3. Results

The results from both searches were organized in groups to show the recurring topics found on legal aspects of Smart House Welfare Technology. The groups include: Smart Houses concept, data privacy, data access and management, stakeholders' interest, and informed consent of the users and/or the users' family .

3. Results

3.1. Smart House Concept

The Smart House project at USN is aimed to help the third age population. As defined by Saranummi [5], the third age refers to those who are retired, alert, and in full possession of their physical and mental capacities. Therefore, the "Smart House" idea is generally used to refer to any living or working environment that has been carefully constructed to assist people in carrying out required activities to promote an independent lifestyle [6,7].

Aging population may be regarded as an opportunity to implement information and communication technologies (ICT) including Smart Houses services. Nevertheless, the rapid development of ICT "should not lead to social exclusion or a widening of the digital divide" [10] .

Some reports have highlighted that technology in Smart Houses or Ambient Assisted Living (AAL) should be: "embedded (non-invasive), distributed throughout environment, personalized (according to users needs), adaptive to the user and user's environment, and anticipatory (anticipating users desires as far as possible) " [8].

Grguric [8] continued to point out that the research and development stage in Smart House systems should include a multidisciplinary approach such as the areas of medicine, law, economics, psychology, and other disciplines dealing with gerontology.

Therefore, a Smart House system should ideally control the functions of the house and interact with the person through voice, movement sensors, hand gestures, touch panels, and other devices. In order to achieve this, the Smart House system needs to adapt to the user's need and adjust the functions according to the user's preference [9].

3.1.1. The Smart House Welfare Technology project at the University College of Southeast Norway

The SHWT at USN aims to automatically monitor the older adult on their activities of daily life (ADL) such as eating, bathing, and sleeping habits [12]. Hence, the Smart House system search for patterns in the user behavior, detects when these patterns break, and warns caretakers in case of potential dangerous situations for additional assistance [13,14].

The system integrates information from sensors, including movement detectors, sonars, temperature sensors, weather stations, switches on doors and windows, among others. The system does not require the use of any device on the body, nor requires the user to modify their daily routines [15]. An important part of the system is a computer vision component that allows the usage of multiple cameras, which work as sensors to extract the position and location of the person, but not as a surveillance system. Only reference images are stored and no person can look at any image or video at any time.

The information collected by the system is mapped into discrete state variables in order to ease the task for pattern recognition, classification, analysis, and modeling of discrete events systems [15]. The data collected includes information from the person, the house, and external weather information. In addition, the activities and behaviors of the system are defined based on possible values of the state variables during sequential time spans and obtained using the system states history [15].

3.2. Data Privacy

Legal regulations should be secured to asses patient-identifiable data [16] in order for the older adult to accept monitoring in a Smart House system. Data storing raises a number of legal and privacy issues that are important to consider. A legal solution should be established for storing data from the welfare technological equipment [17].

The European data protection law states that it is important to clarify how data will be shared, stored in the system, and who will be responsible for such data [18,19]. Also, the Norwegian Health Ministry Act §8 adds to specify [20] :

- Purpose of the processing of health data
- Which kinds of information can be processed
- Requirements for identity management
- Requirements for securing data
- Who is the data controller.

Additionally, the update of the European directive concerning the processing of personal data states that "confidentiality of communications" must be "guaranteed in accordance with the international instruments relating to human rights" [21], fundamental rights, and freedom [22].

Keeping health record journal of the older person is regulated by the Health Personal Norwegian law §39 and §40 [23]. Journal recording from health care professionals forms the legal basis for processing necessary and relevant personal health data. There is, therefore, no requirement for specific consent from patients to allow health personal to keep journal records [17].

Data from sensors are generally regarded as information that does not require journaling. Nevertheless, this information may be important to determine whether the person is in need for health care or not. Consequently, it remains the obligation of the municipality regulation to assess if the service offered to the older person is adequate or if the person is in need for other type of service such as further medical or health monitoring [17].

Moreover, security must be ensured through the communication networks in order to protect the freedom and fundamental rights of the person using the Smart House system, especially regarding the large capacity for automated storage and processing of data [21]. Privacy, confidentiality, and data security are the legal issues that stand out in the area of tele-medicine and e-health [24]. The heterogeneous information that is generated by health care is considered sensitive [25], and thus confidentiality is required.

3.3. Data Access and Management

The Smart House system handles sensitive information. It must be decided who will have legal rights to view the data resulting from the monitoring (surveillance, audiotape, sensor information, and others). Moreover, the data must be secured to keep it from falling into the wrong hands [26].

Security must be ensured, and encryption in the system communication lines must be secured. No third party should have access to the data of the Smart House system, and transmission of the data to external entities must comply with legal requirements [27]. Therefore, it is essential to guarantee that whoever access the information ensures confidentiality [28,6], fully understands the situation, and commits to never misuse the information.

The service provider of the Smart House system should safeguard the security of their services, including the selection of regulated network providers, and inform the user about any risk or breach of security in the communication service of the network [21]. The national legislation in some European member states only prohibits intentional unauthorized access to communications [21].

Moreover, treatment of health and personal information requires a legal basis. Current Norway legislation does not allow the central storage of health information in government auspices (Medical Act §10 [17,29]). A proposed solution that would not require new regulation is to establish national “hosting services” (local data storage) with local ownership that would give voluntary control to store data [17].

Another proposed technical solution is to store data centrally, but separately. This means that health data from various sensors are stored in the same database, but logically separated ensuring that only healthcare working in the same business can access them [17]. Third-party or other stakeholders access to health information from such registry must follow the normal rules for health professionals access to health information (Medical Records Act §10 [17,29]). Also, stakeholders that have signed an agreement on access to health information, as stated in Medical Records Act §19, can directly access the information, while keeping the normal rules for health professionals’ right to disclose health data (the Health §25 and §45) [17,23].

Another legal issue that needs to be addressed is liability for malfunctioning equipment [30,31]. Smart House systems, as any other technology, may carry the risk of failure [32]. Such failures include maintenance in the system, false alarms, and others. Therefore, it is essential for users to be fully informed by the service provider of any security risk or any other type of risk that may lie outside the main scope of the Smart House system [21].

3.4. Stakeholders’ Interests

Regulations need to be standardized to prevent legal issues. Conflicts between the users and the provider of remote care may arise. In a Smart House environment, informal caregivers, relatives, or friends may be often visiting or living in the house with the older person. Thus, it is important to know who are the direct and indirect stakeholders in order to seek consent from them [33].

An important stakeholder is the user/patient himself. In a report by Trill and Pohl [34], the following key tenets of the patient empowerment philosophy regarding e-health were listed: patients cannot be forced to follow a lifestyle dictated by others, preventive medicine requires patient empowerment to be effective, patients, as consumers, have the right to make their own choices and the ability to act on them.

These points need to be taken into consideration during the research and development process. In addition, there are three dimensions of patient empowerment [34], which can also be considered as stakeholders: professional perspective (Doctors, nurses and other health takers), consumer perspective (self-determination of the users through the individual choices they have), community perspective (social inclusion through the development of collective support).

Other stakeholders are goods suppliers and providers, to whom the lack of standardization and misunderstanding of requirements can hinder the development of Smart House systems. Yet, another stakeholder is the organizations working on legal and economic issues, to whom other barriers such as funding, heterogeneous target groups, and lack of standard and certifications, can also hamper the development of Smart House systems [8].

3.5. Informed Consent

According to Demiris [33] “Informed consent is an individual’s autonomous authorization of a clinical intervention or research participation”. The major components of informed consent are competence, disclosure, understanding, and voluntary understanding. The European Parliament also states that consent of a person “may be given by any appropriate method enabling a freely given specific and informed indication of the user’s wishes” [21].

Informed consent must be sought before implementing a Smart House environment. Informed consent in generally signed by patients or subjects that require or volunteer for diagnostic, therapeutic, or research procedure. The providers offering these services or seeking for volunteers for research need to obtain consent from the subjects. The consent includes the social rules that an organization needs to follow during the research procedure.

In Norway, the type of information that is not regarded as health data, such as the data collected by the Smart House system, requires informed consent for its implementation [17]. This includes the processing of data from the welfare technological equipment such as local storage data from the security-creating technologies; for example: fire alarms, security alarms, and fall alarms. Such storage, where information from the equipment is not to be regarded as personal health data in itself, can be based on the user’s consent [17].

In addition, the Smart House system would have the potential to detect early stages of dementia; hence, agreement must explicit detail the ethical and legal aspects to proceed on those cases, and the user must be fully informed [6].

It is important to mention that the Norwegian law on Health Register Act §20 [20] specifies that exceptions exist on the sharing of the health information data. The information may only be disclosed if the person’s treatment is of significant interest to the community, concern for patient privacy and confidentiality are safeguarded, and processing is unobjectionable on ethical, medical and health considerations.

4. Discussion

Smart House Technology is relatively new, but it has a promising future. In Norway, Smart House Technology began in the middle of the 90s, with the BESTA project in Tønsberg [35]. However, the BESTA project stagned [26].

Now, the project at USN aims to develop a Smart House system for older people. The project takes into consideration the legal aspects that can raise when developing a Smart House system. With the development of many new technologies, new laws and regulations need to be established.

Health care personal and nursing homes are provided by the Norwegian government. Thus, welfare technology is also an important part that the Norwegian government needs to standardize. “Morgendagens omsorg” (Tomorrow’s care) in Norway is dedicated to standardize the welfare technology area. Their mission will contribute to integrate Welfare Technological solutions in 2020 as a natural part of the municipal health and care services [17].

In general, the main concern with the implementation of Smart Houses system is the data privacy and management. It has been stated that as long as data confidentiality and security are ensured, there would not be major legal problem [36].

Smart House systems deal with sensitive data that can result dangerous if unauthorized persons have access to it. Thus, it is crucial to have proper legislation that handles the issue of data privacy. In addition, it is important to know who is responsible for what and when [8]. Acts §29 and §30 on Health Register [20] states some charges and penalties against those who violate the processing of health data.

Also, the person who will deal with malfunctioning of the equipment needs to be identified when deploying a Smart House system. The responsible for system failure should be a person who is capable of giving informed consent.

Analysis and assessment of security and legal aspects need to be prioritized when dealing with a wide range of stakeholders, who are prone to responsibility diffusion implementing a Smart House project [37,24]. There should be a special legal framework that handles important questions regarding the role of Smart Houses Welfare Technology for older people. The characteristics, limitations, and permissions in Smart House system should be stated clearly through a set of guidelines and standards [36].

Finally, with Smart House systems in Norway, signed informed consent is always recommended. The person using the Smart House should be capable of deciding on the implementation of such system at his or her own home. Moreover, the person needs to be aware that the system may detect deviation from the usual behavior pattern, and thus alert to caregivers or family if something is wrong.

4.1. Older People Perception and Ethical Challenges

There are also studies that report older people perception on Smart House systems, as well as the ethical challenges that Smart House systems present from a non-legal perspective. These reports include but are not limited to: “Systematic review of studies of patient satisfaction with telemedicine”, “Systematic review of cost effectiveness studies of telemedicine interventions” [38], “A cross-sectional study on person-centred communication in the care of older people: the COMHOME study protocol” [39], “Care work in changing welfare states: Nordic care workers experiences” [40], “Carers’ and nurses’ appraisals of needs of nursing home placement for frail older in Norway” [41], “Ethical implications of home telecare for older people: a framework derived from a multisited participative study” [28], “Senior residents perceived need of and preferences for smart home sensor technologies” [42], “Findings from a participatory evaluation of a smart home application for older adults” [43], “Privacy and senior willingness to adopt smart home information technology in residential care facilities”[44], “A smart home application to eldercare: Current status and lessons learned” [45].

The main concerns on the ethical challenges described on these articles are privacy of the user being monitored, security and reliability in the system, commercial interest, human interaction, and training or learning process for the older adult.

5. Limitations of the study

A limitation of this study is that there are not enough scholar studies on legal aspects regarding Smart House systems in Norway. Therefore, in order to obtain substantial information for this article, we have included articles on recommendations for the implementation of welfare technology [17] and the Norwegian law [29,20,23].

Although Norway is not part of the European Union, we also included European directives and regulations [18,10,22,21] to have a broader picture on how Europe, in general, is legally dealing with new technologies for the older people such as Smart House systems.

6. Conclusions

Smart House technology have proven to be beneficial for improving older adults home care. Statistics in Norway expect that the number of people aged 70 and older will double in the next 30 years [1]. Therefore, Smart Houses development is an important research topic, which will help to cope with the growing demand and supply of nursing care homes.

Norway has almost 10 years of experience with Smart Houses technology as part of home care services [46]. Nevertheless, legal issues are still unresolved. In this article, the legal aspects of data privacy, data access and management, stakeholders, and informed consent, are presented and briefly discussed. Several reports have addressed the legal aspects that Smart House systems present, but the number of studies found are still limited.

In general, the legal aspect of Smart House systems is a significant barrier that may impede their widespread adoption. Thus, there is the need for standardization, research, surveys and assessment on the legal aspects that Smart House systems convey in order to provide evidence for optimizing the use of this promising technology.

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Conference Article 4

Welfare technology, healthcare, and behaviour modelling-an analysis.

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16th International Workshop on Intelligent Environments: Supporting Healthcare and Well-being (Workshops). 2019

DOI: 10.3233/AISE190057

Intelligent Environments 2019
A. Muñoz et al. (Eds.)

doi:10.3233/AISE190057

Welfare Technology, Healthcare, and Behaviour Modelling- An Analysis

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Abstract. Welfare technology is a growing area of research due to the increase in the ageing population. In Nordic countries, public authorities are the primary healthcare providers. Therefore, there is significant of investment to help older people to live as long as they wish at their own home. At the University of South-Eastern Norway, a current project on welfare technology is being developed for this purpose, with a focus on human behaviour modelling. Through the research, gaps were found between the technology and the healthcare aspect of it. Consequently, difficulties for the consumer (the older people) arise. This article presents an analysis of connection and gaps between technology and the healthcare area of welfare technology for the ageing.

Keywords. ambient assisted living, smart house, ageing in place, intelligent environment, Norway, assistive technology

1. Introduction

Welfare technology for older people has dramatically grown in the Nordic countries [1]. The reason for this interest is due to the increase in the ageing population, not only in Nordic countries but also in European Union (EU) member states, European Free Trade Association countries (EFTA: Iceland, Liechtenstein,Norway, and Switzerland), and candidate countries (Albania, the former Yugoslav Republic of Macedonia, Montenegro, Serbia and Turkey) [2].

In Norway, as of 2019, life expectancy increased for both men and women. In addition, 38% (one in five persons) of households are composed of people living alone. By 2060, 20% of the Norwegian population will be 70 and older compared to the current 11% [3]. Fig 1 shows the population projection for Norway. Similarly, in the EU, those aged 80 and over will almost double from 5.5 % to 12.7 % between 2017 and 2080 [2]. Figure 2 shows the population projection for the European Union.

A common approach to help older people to stay at home for as long as possible is smart houses, sometimes referred to as ambient assisting living. The general aim is to assist the older person in case of need, while other studies focus mainly on fall detection [4–7].

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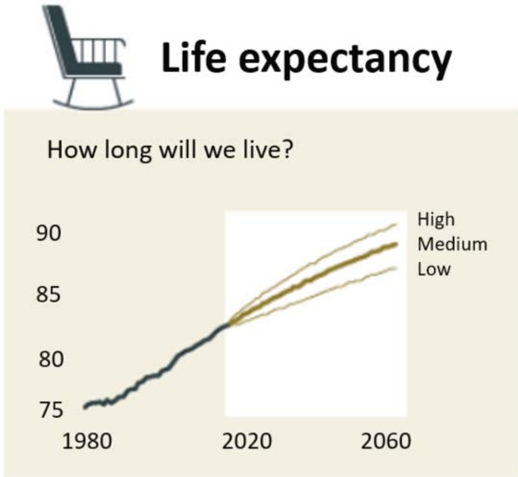

Figure 1. Norway population projections [3]

At the University of South-Eastern Norway (USN), a current project on welfare technology is being developed to help the older people to remain at home for as long as they wish [8,9]. The main focus of the research is on human behaviour modelling (HBM) to ensure the older person lives in safe and dignified conditions. The HBM's goal is to detect anomalies on the person's behaviour pattern and assist if needed.

As part of the same project at USN, the healthcare aspects and older people's perception of welfare technology are also being researched [10]. The contribution between the two areas - technical and healthcare - has shown that regardless of the amount of research in welfare technology for older people, breaches are still found. There are limited studies addressing this topic [11]. Therefore, this article presents an analysis of the gaps between the technology and healthcare aspects when implementing welfare technology for the ageing.

This study's main contribution is towards helping future researchers to connect and consider both sides - the technology and healthcare - when developing welfare technology for older people.

1.1. Aim

The study aim is to discuss the connections and gaps between the technology and healthcare fields when developing welfare technology for older people.

The remainder of this article is presented as follows: Section two introduces the background and reviews the related work. Section three describes the methodology. Section four defines the terminology generally used in welfare technology for the ageing. Section five presents the analysis results. Section six provides recommendations. Finally, the conclusions are given in section seven.

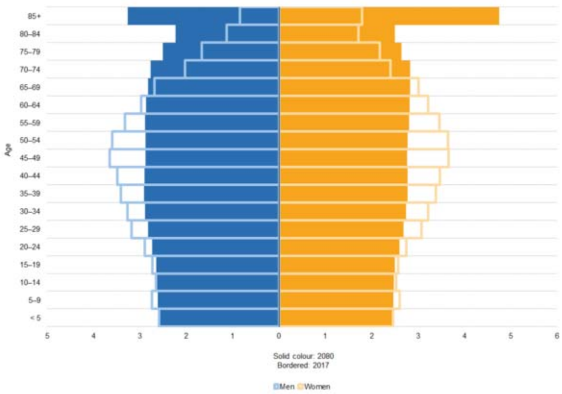

Figure 2. Population pyramid EU-28, 2017 and 2080 (% of the total population) [12]

2. Background

Several studies have been conducted in the area of smart house environments with various reviews in this field available [4, 7]. In the field of healthcare involving smart houses, several research have been made to study older people's perception of smart houses [13–15].

Most of the research in smart houses from the technological aspects deals with improvement, new technology implementation, and activity detection to adapt the smart house to the user. Among the relevant works is the Managing an Intelligent Versatile Home (MavHome), whose goal is to increase the comfort of the users and reduce the operation costs [16]. The "GatorTech" smart house implements several smart devices to "optimize the comfort and safety of an older person" [17].

User activity detection has widely been researched, and several analysis methods have been used [4]. In summary, the analysis methods range from pattern recognition algorithms and computer vision [18],machine learning [19, 20], statistical models [21, 22], among others. However, only a few studies have been conducted in behaviour modelling [9, 23–26].

The studies that have been done in the healthcare area usually report about the ethical concerns on smart houses or older people's opinion about smart houses [15, 27]. There are, however, gaps between the technology and the healthcare research regarding welfare technology. As a result, the end-user (the older person) is ultimately the one who is affected because of these gaps.

3. Design and Methods

An analysis was chosen in this study to report the findings. Initial comparison in the terminology used between the technology and healthcare fields are discussed. Secondly, an analysis of the terminology, healthcare with a focus on the person, ethical and legal challenges, and older people's struggle with technology are discussed. Finally, some recommendations are provided to diminish the gap between the two fields.

4. Terminology

There is a lack of standard definitions for the terms used in smart house welfare technology for the ageing. In most research, the terms ambient assisted living (AAL), smart houses, home automation, welfare technology, ambient intelligence, and others have been used interchangeably.

However, in the area of healthcare, the definition of terms is essential for them. A possible reason could be the use of the MeSH (Medical Subject Headings) terms. As defined in [28], "MeSH is the National Library of Medicine's controlled vocabulary thesaurus, used for indexing articles for the MEDLINE/PubMED database", which means that most article citation is related to a specific set of MeSH terms. The purpose of the MeSH terms is to focus on relevant citations when doing a search of literature. In contrast, keywords search does not narrow down the most relevant citations in a search.

The term's definition is the first difference between technology and the healthcare field. Thus, while healthcare research generally focuses its work with MeSH term, those working in technology use typically keywords.

In this section, the most common terms are defined to provide a guide on the meaning of the following concepts: welfare technology, AAL, smart house, activity recognition, and behaviour modelling.

4.1. Welfare Technology

In Nordic countries, the term welfare technology is commonly referred to as the type of technology used to control the environment, safety, and general well-being of the older or disabled people [29]. The goal is to provide the older person with the option to live as long as possible in their own home. As mentioned in the introduction, the Nordic countries face demographic challenges with the growing older population. Thus, welfare technology seems the optimal solution to this challenge.

The term "welfare technology", as it is, cannot be found in MeSH. Rather, the term "welfare" comprises child, animal, social, and maternal. Therefore, although welfare technology has widely been used in the technology field, healthcare science has not yet introduced proper definition through MeSH for it.

4.2. Ambient Assisted Living

As defined by Rashidi, "Assisted living technologies based on ambient intelligence are called ambient-assisted living (AAL) tools" [30]. This term yet implies defining ambient intelligence, which refers to digital environments that are sensitive, adaptive, and responsive to human needs [31].

AAL is thus regarded as an umbrella term for most welfare technology used to help older people. Ranging from pill reminders [32], improving safety in general, fall detection systems, house automation, monitoring such as video surveillance, and activities of daily life (ADL) recognition.

Although AAL does not appear in MeSH, two other terms are found. The first, "assisted living facilities" is defined as "a housing and healthcare alternative combining independence with personal care. It provides a combination of housing, personalized supportive services and healthcare designed to meet the needs, both scheduled and unscheduled, of those who need help with activities of daily living".

The second term, “independent living” is defined as “a housing and community arrangement that maximizes independence and self-determination”. Both terms were introduced in 2003 and 2010 respectively.

It is worth noting that the terms: living independent, community dwelling, and ageing in place, are also used in healthcare as synonyms for independent living.

4.3. Smart House

According to a review on smart houses welfare technology, “Smart house commonly refers to any living or working environment carefully designed to assist residents in carrying out daily activities and to promote independent lifestyles” [7,10]. The general goal is to adapt the house to the occupant’s preferences.

When searching in MeSH , there are two terms found. The first term is from 1992, “housing for the elderly”, defined as “housing arrangements for the elderly or aged, intended to foster independent living. The housing may take the form of group homes or small apartments. The concept includes housing for the elderly with some physical limitations”.

The second term is from 1968, “homes for the aged”, defined as “geriatric long-term care facilities which provide supervision and assistance in activities of daily living with medical and nursing services when required”.

Synonyms found in the healthcare sciences for housing for the elderly are: retirement life care centers, continuing care retirement centers. In the same way, the synonym for homes for the aged is old age homes.

4.4. Activity Recognition

Activity recognition has been implemented for several decades [4]. People usually tend to follow a pattern in their daily life [33,34]. Hence, recognizing the pattern of the person helps to adapt a smart house to the inhabitant.

Commonly, the actions recognized are activities of dalily life (ADL), such as sleeping, toileting, showering, dressing, eating, etc. These are actions that require “basic skills and focus on activities to take care of one’s own body” [35]. By finding repetitive patterns on the person’s activity, it is possible to predict the next activity of the person for assistance if needed [5].

4.5. Behaviour Modelling

There is a few studies on behaviour modeling as described in section 2. Yet, the term behaviour has not been fully defined as the previous terms presented in this section. At USN, behaviour is defined as the activity, duration, posture, and location of the person. E.g., having breakfast. Thus, a behaviour is an activity with duration [8,9].

HBM helps to predict the next behaviour of the person and thus adapt better the smart home to its resident as well as construct a safer environment. In addition, modelling the behaviour of the person allows detecting any anomaly on the person’s daily pattern. “Anomaly detection refers to the problem of finding patterns in data that do not conform to expected behaviour” [36]. Detecting anomalies can help alert family members or caretakers in case of dangerous situations such as falls.

The terms “activity recognition” and “behaviour modelling” are not found in MeSH, as expected. Probably because both terms are not of relevant use in healthcare science. Table 1 shows terms defined in this section and compared to the MeSH terms.

Table 1. Terminologies used in the technology field compared to the MeSH terms

Technical term	MesH term
Welfare technology	not found
AAL	assisted living facilities, independent living
Smart house	housing for the elderly, homes for the aged
Activity recognition	not found
Behaviour modelling	not found

5. Analysis

Studies show that older people would benefit from smart house welfare technology in the areas of health, safety and security, peace of mind (for the family), independence, mobility, and social contact [37]. Therefore, developing smart houses is important for older people.

The works related to welfare technology for the ageing usually refer to either the technical part or the healthcare part of it. It is not easy to find studies were both areas are deeply integrated.

5.1. On the Terminology Used

Section 4 defines the terms used in the technical field and compares them to the terms used in healthcare. The terms that were found in both areas fit mostly the same meaning and are used similarly. However, it is possible to notice that healthcare science emphasizes a proper definition, unlike the technology field.

Typically, most technology researchers do not accentuate the need for a single definition for the terms they use. Thus, when doing a state-of-the-art search, a significant number of keywords with synonyms need to be used. As a result, important research in the field can be left out if the correct keyword is not used. Healthcare science reduces the stress of finding keywords and synonyms by using MeSH terms.

It is worth noting that the technology field needs to find new terms if there is not any term currently available. However, welfare technology has been around for the past decades, and thus moving towards a definition of the terminology should be on the mind of the technology researchers.

5.2. On the Healthcare Focus on the Person

Welfare technology aims to help the user, which presents another difference from healthcare research that centres on the person. At USN, the healthcare research program focuses on “person-centred values and principles like respect, autonomy, participation, justice, dignity, trust and patient safety and rights" [38]. Respecting the individual is one of the main principle of person-centred research [39]. Therefore, the term "user" should be avoided when referring to the older person in the welfare technology context.

Person centred means "putting the person in the centre (not in the middle) as a necessary condition for proper care and good and efficient healthcare services" [40] and " standard of care that ensures the patient/client is at the centre of care delivery" [41].

Taking these concepts into consideration, it is here where technology researchers usually fail. Most technology researchers do not consider what the older person needs or desires, even if that is the goal of welfare technology. Previous works have pointed out that the end-user is usually forgotten because technology researchers focus merely on the technical aspects, thus neglecting the aim of helping the user in their daily life [11].

A reason for this could be that technology researchers do not always have the opportunity to work directly with older people. On the other hand, some technology researchers may not look forward to work directly with people.

Working with people is not always an easy task for technology researchers. Usually, technical education does not involve how to approach people, especially older people. Inquiring about what the older people needs are to develop welfare technology does not imply just asking "what do you need?". Instead, it takes a trained person in conducting interviews to obtain the correct information needed. This is where the healthcare researchers can help technology researchers.

In addition, healthcare science focusing on the person can make sure the older person's needs are placed before the needs of the researchers, industry, government, or any other party involved.

Special attention needs to be paid in the topic of learning the behaviour of the older person in a smart house. HBM could be invasive in many ways to the older person. Their privacy and space need to be respected. It is here where placing the older person in the centre is crucial to provide a dignified environment for the older person.

Nevertheless, healthcare and technology researchers may find difficulties to communicate with each other. Technology researchers assume many things that may be unknown to the healthcare researcher, and vice versa, which may grow into frustration from both sides.

It should not be presumed that either the technical field is more relevant than the healthcare field when developing a welfare technology. Both areas cannot be separated if the final goal is to improve the lives of older people. Therefore, there should be more collaboration between both fields.

5.3. On the Ethics and Legal challenges

The ethical part is an important aspect when developing welfare technology due to the several challenges that arise. These challenges range from cost-effectiveness, privacy, autonomy, informed consent, dignity, safety, and trust. Other concerns are the legal aspects, technology acceptance, exclusion, depression and isolation, the gap between designers and users, and technology testing and assessment [10].

At USN, these ethical issues are considered in order to provide a safe and dignified environment for older people. However, technology has limitations and thus cannot solve all the problems related to ageing [10].

The legal aspects are another essential part of welfare technology. Although countries have different laws involving welfare technology, the concerns tend to be the same for most countries. Generally, the main concerns regarding legal issues are data privacy, data access and management, informed consent, and stakeholders' interests [42]. Some studies report that if data confidentiality and security are ensured in a smart house welfare technology, then no major legal problems should arise [43].

In Norway, the municipality is responsible for providing care services to its residents [42]. Among these services are offering home health care, practical assistance for daily tasks, and residence in nursing homes. Due to the shortage of nurses [44] and the government investment in welfare technology to cope with it, Norway is moving towards standardizing welfare technology and is called "Morgendagens omsorg" (tomorrow's care) [45].

Finally, it is important to mention that there should always be user feedback in the research and development (R&D) stage. Older people's feedback can reduce possible errors in the product [46]. In addition, rejection from older people can be avoided if their feedback is taken into account from the beginning [47].

5.4. On the Older People Struggle with Technology

Traditionally, human computer interaction (HCI) refers to how the person (user) interacts with computers. However, with the increase of technology to the personal level, this area has extended to human-centered informatics [48].

To achieve the full potential of welfare technology, HCI should be considered. Unfortunately, most researchers disregard this. As a result, the final interfaces or products do not accommodate the needs of older people [49].

It is thought that older people struggle with technology, but this claim needs to be addressed, not only stated. Indeed, a study suggested that older people struggling is only a stereotype and that older people are open to trying new technology [50]. Therefore, if technology researchers believe that older people have difficulties with technology, then more exploratory studies need to be performed to find out why older people tend to struggle with technology - instead of hoping for the newer generation to use welfare technology in the future.

Finally, it is worth noting that older people's difficulties vary according to generation and place. Nevertheless, understanding why older people struggle should not be omitted; otherwise, welfare technology will always be a challenge for current and future older people [50].

6. Recommendations

In this analysis, the connection and gaps between technology and healthcare field within welfare technology area were discussed. Technology researchers generally assume that the needs of older people are house automation or fall detection. While it is true that older people would appreciate not lying on the floor for hours, many of them think that falling is not something that would happen to them. Therefore, it is necessary to find out what other requirements older people have. Technology researchers have to consider older people's needs by making the older person a priority by placing the older person in the centre.

Technology researchers find it easier to a design welfare system that will solve their own needs, even if they do not realize it. It is harder to design for another person whose needs are not the same as the researchers' need.

Older people's needs are not always easy to know. Therefore, it is essential that researchers study older people's need according to the place where welfare technology is being developed. Through the help of the healthcare field, a major understanding of the needs and struggles of older people can be achieved.

In addition, when learning about human behaviour, the collected data contains sensitive information. Consequently, many ethical and legal issues need to be addressed. It is not possible to propose a final solution for welfare technology for older people unless the ethical and legal issues are discussed.

The technology and healthcare field should not work independently if a stronger improvement in welfare technology for older people is desired.

7. Conclusion and Future Work

Throughout this study, the gaps found between technology and healthcare were presented, analysed and discussed. Several studies point out these issues, but they have not been fully addressed and thus are still a current problem.

Four important issues found need to be addressed when developing smart houses: terminology, placing the older person in the centre, approaching the ethical and legal aspects of it, and considering the struggle older people face with welfare technology.

In the field of welfare technology for older people, these issues affect the older person directly. Therefore, stating these gaps should no longer be an option for welfare technology developers. Instead, addressing them and solving them should be the next step if improvement is wanted.

Future work should focus on reducing these gaps by doing more collaboration between the technology and the healthcare field. This can help reduce the ethical and legal issues, the struggle with technology that older people may face as well as improve their safety and respect their dignity.

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Doctoral dissertation no. 63
2020

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Human Behaviour Modelling for Welfare Technology

Dissertation for the degree of Ph.D

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Veralia Gabriela Sánchez H.

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ISBN: 978-82-7206-548-4 (print)
ISBN: 978-82-7206-549-1 (online)

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