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Evaluierung von Systemen zur Sturzprävention und -detektion

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System evaluation for fall detection and prevention

DIPLOMA THESIS

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in

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Erklärung zur Verfassung der Arbeit

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Wien, 30. August 2019

Jennifer Lumetzberger

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Kurzfassung

Durch die immer älter werdende Population steigt auch die Anzahl an pflegebedürftigen Menschen. Produkte werden entwickelt, um ältere Personen bei einem selbstbestimmten Leben zu unterstützen. Geräte zur Erkennung und Prävention von Stürzen sollen das Risiko für Verletzungen und Todesfälle durch Stürze verringern, das gerade bei älteren Menschen höher ist. In der vorliegenden Arbeit werden Systeme zur Sturzprävention und -erkennung evaluiert. Für den Vergleich von Geräten zur Sturzprävention werden der bildbasierte Sensor *fearless*, der Bewegungssensor *Optex* und zwei verschiedene Varianten des druckbasierten Systems *Bucinator* herangezogen. Im Zuge eines vierwöchigen Feldexperimentes mit vier Probanden werden 239 Aufsteh-Ereignisse gesammelt und ausgewertet. Für die Evaluierung der Systeme zur Sturzdetektion werden 11 Sturzszenarien und 11 Aktivitäten des täglichen Lebens mit 10 Probanden simuliert. Die *iWatch4* von Apple wird mit dem stationären Sensor *fearless*, der mobilen Applikation *b-cared* und dem beschleunigungsbasierten Anhänger *sturzmelder* verglichen. Für die Bewertung des Alarmverhaltens der Geräte zur Sturzerkennung und -detektion werden die Sensitivität und der positive Vorhersagewert berechnet. Während *fearless* mit 92.93% die größte Anzahl an Aufsteh-Events erkennt, sind es 76.67% für den *Bucinator Paulus*. Die Fehlalarmrate liegt mit 15.00% der detektierten Alarme bei *Bucinator Paulus* niedriger als bei *fearless* (32.47%). Alle Geräte zur Sturzerkennung senden einen Alarm innerhalb von 30 Sekunden, wodurch die gesundheitlichen Folgen nach einem Sturz minimiert werden können. Eine Umfrage, basierend auf einem Akzeptanzmodell, wird verwendet, um die Nutzerakzeptanz für AAL Geräte und im Besonderen für Systeme zur Sturzerkennung und -prävention zu erheben. Durch die Übertragung der Dimensionen des Akzeptanzmodells auf Fragen im Fragebogen können Aussagen zur Nutzerakzeptanz getroffen werden. 189 Antwortbögen werden untersucht, wobei sich die Teilnehmer auf folgende Gruppen aufteilen: Pflegepersonal, Management im Gesundheitswesen, Personen im Alter 65+ und Angehörige. 70.81% aller Teilnehmer denken, dass AAL Technologien ihre Leistung im Job oder den Alltag erleichtern können. Der Unterschied zwischen der Beeinflussung der Privatsphäre durch bildbasierte und nicht-bildbasierte Methoden wird eruiert. Auch wenn bereits ein erster Schritt zur Erstellung einer Messmethodik für den Eingriff von Technologie in die Privatsphäre gesetzt ist, konnte kein quantitativer Ansatz zum Vergleich von verschiedenen Produkten gefunden werden. Das Senden von GPS Daten, Videos oder Bildern, als auch die Aufnahme von Audio- Daten kann als Privatsphären-Verletzung gesehen werden und hängt von der Wahrnehmung des Nutzers ab.

Abstract

As the world's population is becoming steadily older, the number of people in need of long-term care increases. With rising costs and the people's wish for more autonomy, more devices supporting elderly people in everyday life are designed. Since falls leading to death are more likely to happen to the elderly, products enabling early help in falls or even preventing falls are coming into the market. This work compares chosen devices for fall prevention and fall detection. For the evaluation of fall prevention devices, the image-based sensor *fearless*, the motion sensor *Optex* and two versions of the pressure-based system *Bucinator* are used. After a 4-week field trial with 4 participants, 239 getup events are obtained and analysed. The assessment of devices used for fall detection is done in a laboratory setting comprising 10 subjects, simulating 11 fall scenarios and 11 Activities of Daily Living. The *iWatch4* from Apple is compared with the *fearless* sensor, the mobile application *b-cared* and the accelerometer-based device *sturzmelder*. The precision and recall are calculated to evaluate the alarm behaviour of the fall prevention and fall detection devices. Speaking of fall prevention, *fearless* detects the most falls (92.93%), while it is 76.67% for the *Bucinator Paulus*. The mean false alarm rate of all detected alarms is for the *Bucinator Paulus* 15.00% and for *fearless* 32.47%. All of the tested devices used for fall detection send an alarm in under 30 seconds, which helps to minimize the health impact after a fall. With an adapted acceptance model, a questionnaire is performed to rise the user acceptance for AAL devices and in particularly for sensors detecting and preventing falls. 189 reply forms are evaluated, dividing the participants into the following groups: nursing staff, healthcare management, relatives and users aged 65 and older. 70.81% of all participants think that AAL technology will increase their job performance or facilitate things in everyday life. Image-based and non-image-based devices are analysed in terms of differences in the degree of privacy intrusion. Although researchers have made first steps towards a measurement of obtrusiveness, no metrics could be found to rate different devices. Audio recording as well as sending GPS, image and video data can be regarded as intrusive and is dependent on the user's perception.

Contents

CHAPTER 1

Introduction

Due to the demographic change, the population is becoming steadily older (see Figure 1.1) [1]. Thus, the number of people in need of long-term care increases [2]. As the amount of required beds and health workers in healthcare facilities is rising, the costs are increasing too [2]. Based on a study initiated by the Austrian Fiscal Advisory Council, the average annual growth of care costs in Austria for 2015 until 2030 is estimated to lie between 4.4 and 6.2 percent [2]. Apart from the economical issue, the demographic change leads to challenges concerning the quality of life for elderly people and their carers and to impacts on the labour market [3]. The Active Assisted Living (AAL) market has

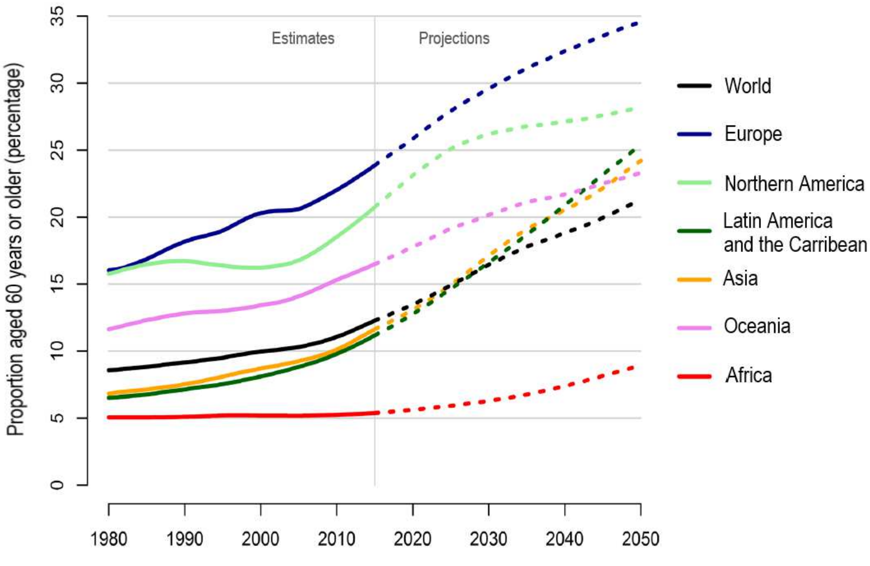

Figure 1.1: Percentage of population aged 60 years or over by region, from 1980 to 2050. (Image from [1])

potential to face these challenges [4]. AAL technologies shall help elderly people to live self-determined and to stay at home instead of living in care homes [5].

1.1 Problem Presentation

Dependent on the type of device, AAL technologies support elderly people in various aspects of life, like fitness, health, communication and injury prevention [6]. AAL devices cannot only be useful when installed at home, they can also have a positive impact when used in care homes [7]. The following work investigates methods to compare AAL technologies and focuses on fall prevention and detection. This is because falls are a major public health issue, with disabling physical and psychological consequences [8, 9]. Assisting people when getting out of bed and fast reactions to falls can help to reduce costs [10] and the risk of injury [11]. Reviews on the performance of fall-related technology focus on a specific category or provide information about technologies, challenges and trends only [12]. Others do not address currently available products [13, 14]. To approach these gaps, this thesis compares image-, motion-, pressure- and accelerometer-based technologies for fall prevention and detection. Along with more autonomy, using AAL devices goes along with a loss of privacy [15]. The suspicion of image-based technologies intruding people's privacy is particularly high [16]. Thus, the question, whether the impact on a patient's privacy differs between vision-based AAL systems and technology based on other methods, is discussed. In terms of vision-based systems, multi-camera devices like the Microsoft Kinect, which combines an RGB and a depth camera (then called RGBD camera), and methods using one single camera are distinguished [17]. The type of camera influences the degree of intrusiveness [18]. RGB sensors provide truecolor images of a person, depth images deliver information based on the distances between objects, while infrared images represent the temperature distribution of the visualized scene (see Image 1.2).

Figure 1.2: Depth, infrared and RGB image, from left to right. (Image from [19])

A key factor for the use of AAL is the user acceptance, which is described by different models, such as the Theory of Planned Behaviour (TPB), the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [20]. The benefits of using technology as well as the effort associated with using a system are only two factors influencing the user acceptance [20].

1.2 Aim of the work

In the course of this thesis, the following research questions are examined:

- How can different AAL technologies be compared?
- How can user acceptance of AAL technologies by different user groups be measured?
- Does the impact on a patient's privacy differ between image-based and non-image-based AAL technologies?

For answering these questions, the following aspects are considered:
1) Performance: how is the performance of different AAL systems in terms of measurable numbers? Which other factors are relevant for comparing them?
2) Acceptance: are the systems accepted by the users/care workers/technical staff/heads of nursing homes/relatives? Is a loss of privacy accepted if there is an increase in life quality? By which means user acceptance can be measured?
3) Necessity: what is the medical benefit of the AAL device?

1.3 Methodological approach

The methodological approach comprises the following parts: At first, a literature search on fall-related technologies is done. Information about different devices and the handling with the privacy issue is gathered.
In a next step, studies on the medical necessity of such systems are investigated. A possible correlation between the time passing from a fall happening and a health worker finding the person with the extent of the injury is analysed. Further, the frequency of people falling is raised.
The acceptance of AAL technology, especially of fall prevention and detection systems is investigated. Therefore, methods for measuring user acceptance are analysed and applied. A survey is conducted to find out about the claims for AAL systems. Furthermore, the acceptance and the role of autonomy and privacy are evaluated. These aspects shall be regarded from different points of view (health workers, technical staff, healthcare management, people over 64 and their relatives).
For the performance evaluation, tests are conducted in a laboratory environment as well as in a field trial. For the latter, chosen systems are installed in a cooperating care home. The time points of the alerts sent by the devices are compared with the time the correspondent behaviour occurs. Fall detection systems are tested in the lab environment for receiving a higher number of falls than it would be possible in a field study. The devices are analysed regarding performance, costs, installation effort, maintenance effort, time delay, privacy intrusion and size. To evaluate the performance, precision and recall are calculated and compared. The following is hypothesized:

- The extent of an injury increases with the time between a fall and the arrival of help.
- User acceptance relies on multiple factors and cannot be directly measured.
- Elderly people regard image-based systems as more privacy intruding than non-image-based devices.

1.4 Contributions

The main contributions of this thesis include the following:

- A field study with four participants is carried out, comparing *fearless - the intelligent fall sensor*, *Bucinator Paulus*, *Bucinator Vivus* and *Optex EX-35r*. 239 getup events are extracted from a set of depth image sequences, whose time stamps are compared with the alarm time of the devices.
- The *iWatch4*, *fearless*, *sturzmelder* and *b-cared* are evaluated in a laboratory environment with 10 subjects simulating 11 fall scenarios and 11 Activities of Daily Living.
- The investigation of fall detection and fall prevention devices comprises performance, time delay, privacy obtrusiveness, battery life, installation and maintenance effort, price and size.
- A questionnaire based on the UTAUT2 model is designed and evaluated, with 189 participants split into the following groups: nursing staff, technical and management staff in healthcare facilities, users aged 65 and older, and relatives.

1.5 Structure

This thesis is structured as follows. Chapter 2 points out why the point in time of help in falls is important, while considering the definition of a fall, the frequency of people falling and special risk factors for elderly people. The term AAL is introduced, and several methods for detecting and preventing falls are presented, dividing them into image-based and non-image-based approaches. Furthermore, the meaning of privacy in the context of AAL is described and different user acceptance models are demonstrated.
Chapter 3 depicts the utilised methodology, comprising the chosen products for the evaluation, the metrics used for comparing them and the setting for both the fall prevention and fall detection tests. Based on the chosen acceptance model, a survey is created which is presented in this chapter too.
In Chapter 4, the results of the products evaluations are presented and compared using precision and recall as metrics. Additional factors like time delay, battery life, installation and maintenance effort as well as the price, size and privacy protection are analysed.

Finally, the outcomes of the survey are demonstrated and discussed.
Chapter 5 closes the work with a conclusion and a view on future work. Figure 1.3 summarizes the main tasks of this thesis.

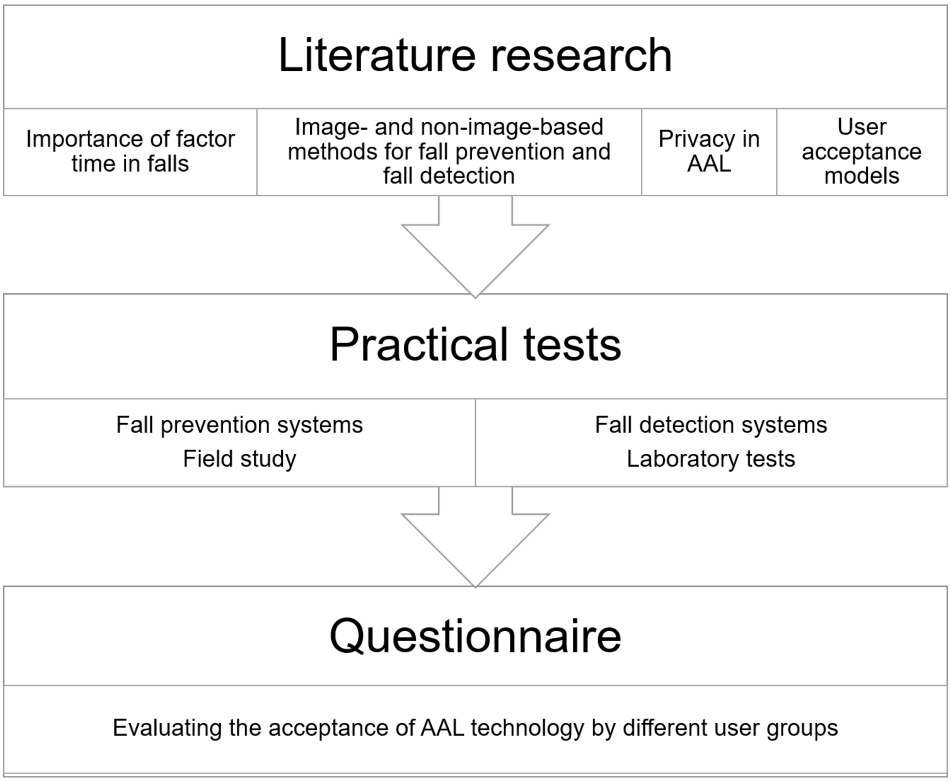

Figure 1.3: Workflow of this thesis.

CHAPTER 2

Related Work

As the population is getting older [1] and the risk of falls increases with age [21], a research division of AAL focusing on fall recognition and prevention has evolved [22]. The European Next Generation Ambient Assisted Living Innovation Alliance (AALIANCE2) determines the application area of fall prevention technology to range from moving safely at home and outdoors to preventive motor training and system recognition of dangerous situations [23]. Fall recognition technologies provide support by contacting care givers and informing them about a fall [23]. This chapter presents methods for fall prevention and fall recognition. Ways how to describe and evaluate user acceptance and how these can be applied to AAL are explained.

2.1 Falls statistics

When speaking about falls, the definition of the term is not uniform [24]. The Kellogg International Work Group on the Prevention of Falls by the Elderly [24] highlights the problem of unlike definitions to be the reason for inadequate comparisons between fall studies. Zecevic et al. [25] show that seniors associate falls with losing balance while healthcare providers generally describe a fall in the context of its consequences. Researchers tend to think of it as the event itself [25]. Although a unique definition may not be necessary, the communication of what is regarded as a fall is essential [24]. A commonly used definition is the one of the Kellogg Group, which describes a fall as "an event in which a person unintentionally comes to rest on the ground or other lower level and other than as a consequence of the following: sustaining a violent blow, loss of consciousness, sudden begin of paralysis, as in a stroke or an epileptic fit" [24].

2.1.1 Frequency of people falling

About 28-35% of people aged 65 and over fall each year [26, 27]. This percentage rises to about 32-42% in people over 70 [28, 29]. Generally, the frequency of falls increases with age [21] and frailty level [30]. 20-30% of falls lead to mild to severe injuries, and form 10-15% of all emergency department visits [31]. Over 50% of injury-related hospitalizations are among people over 65 years [32]. Figure 2.1 shows that especially fatal falls (falls leading to death) are more likely to happen to elderly people. This trend is also reflected in other studies, such as of the Department of Health and Human Services of the United States [33] and of the World Health Organization (WHO) [34].

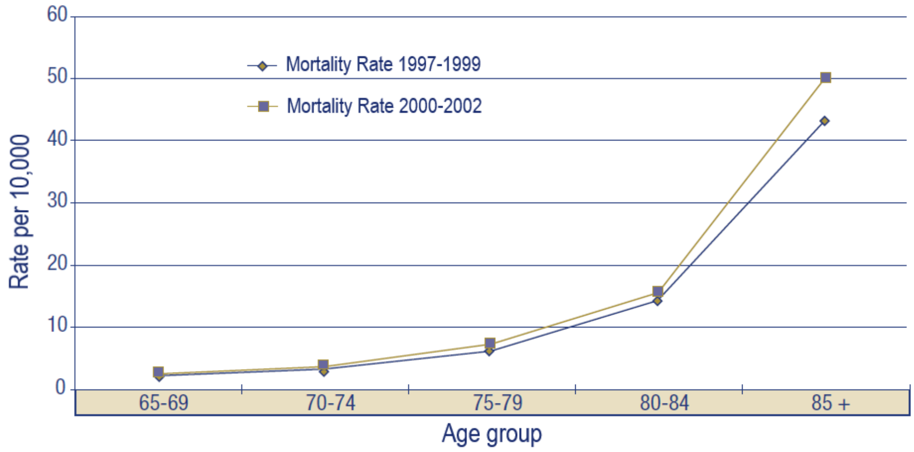

Figure 2.1: Mortality rate due to falls by age group in Canada. (Image from[32])

Kannus et al. [35] investigate fall-induced deaths among the elderly population in Finland [35]. They have found out that the number of fall-induced deaths for Finns above age 50 has more than doubled between 1971 and 2002. As the population becomes older, a rising number of similar deaths is predicted in Finland and other Western populations [35]. Apart from health concerns, another major issue arising from this trend are costs [34]. In 2015, approximately 50 billion US dollars were spent on medical costs resulting from fatal and nonfatal falls in the United States [36]. Due to the ageing population, the costs are assumed to be rising [36]. Kannus et al. [37] predict that by 2030, fall-induced cervical spine injuries in Finns aged 50 years or older will be about 100% higher than they were during 2000-2004.

2.1.2 Reasons of people falling

In order to develop solutions to reduce the number of falls, analysing the reasons of falls is important [34]. The main risk factors can be categorized into four groups: biological, behavioural, environmental and socioeconomic factors [34, 32]. Examples for each risk factor group can be seen in Figure 2.2. Along with age and physical handicaps, inappropriate footwear and poor building design can also lead to falls [34].
With an increasing exposure to these risk factors, the chance of falling rises too [34]. The Canadian Community Health Survey done in 2005 analyses the type of activity people aged over 65 reported when falling resulted in injury [32]. 44% slip, trip or stumble on any surface and 26% fall while going up or down the stairs [32]. 47% of falls within

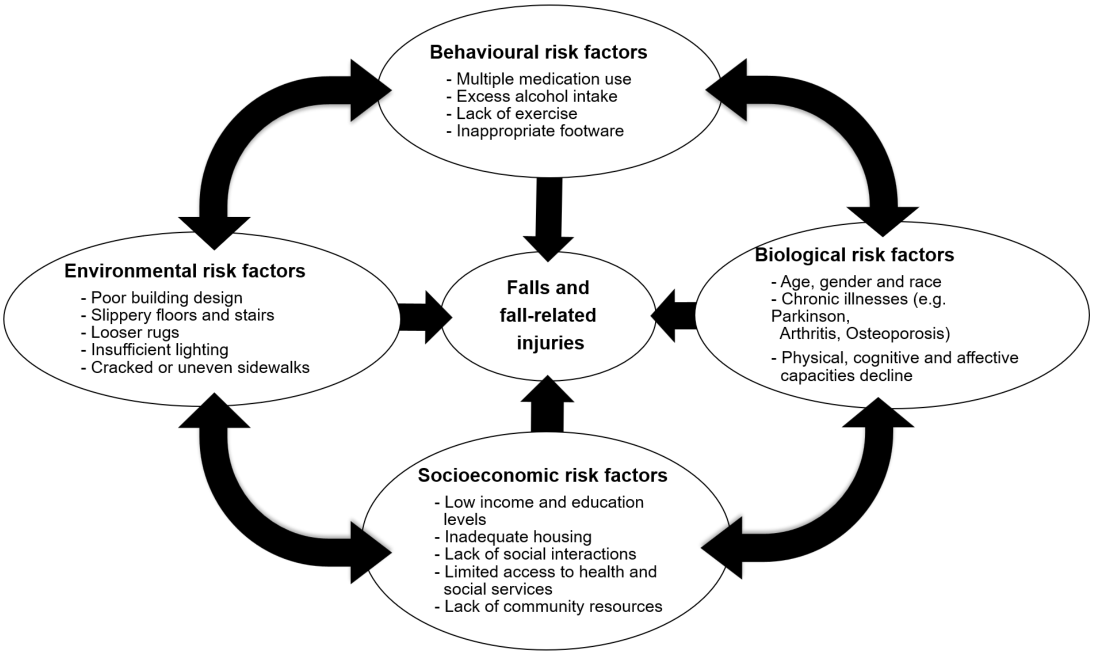

Figure 2.2: Risk factors for falls in older age. (Image from [34])

the same age group treated in hospital happened at home [32]. The San Diego County Elderly Falls Report from 2005 confirms this result [38]. In the years 2000 and 2001, 56% of fall injuries in the age group above 55 happened at home [38].
Elderly people living in residential care fall about three times more often than those living in the community [39]. About 30-50% of all residents in long-term care fall each year, of which 40% fall twice or more each year [39].

2.1.3 Importance of early help in falls

Gurley et al. [11] perform a study about people found helpless or dead in their homes by the San Francisco emergency department. This paragraph refers to the work of Gurley and colleagues [11]. 367 persons with an average age of 73 years were found, of which 23% were found dead and 5% died in the hospital. The frequency of such incidents was found to increase sharply with age. Men above 85 years who were living alone had the largest share (123 per 1000 per year). The research team demonstrates that the mortality rate correlates with the time a person has been helpless for. For patients who have been helpless for more than 72 hours, the mortality rate was 67%, while it was 12% for patients who waited for help less than one hour. After being found helpless, the majority of patients was unable to return to independent living.
Wild et al. [40] focus especially on falls of elderlies at home. This paragraph refers to the work of Wild and colleagues [40]. Over a period of one year data of 165 people aged 65 and older who fell at home was collected and compared with a control group. 20 persons

were unable to get up by themselves for more than one hour, and four of them stayed on the ground for more than six hours. The subjects were visited within seven days after the fall, and again after three and twelve months. After one year, 32 fallers had died compared with eight participants from the control group. Half of those who were helpless for more than one hour died within six months.

2.2 Active Assisted Living

Active Assisted Living (AAL), or the previous term 'Ambient Assisted Living', is a concept aiming to enable individuals to live an active, socially involved and independent life up to an old age [4]. Therefore, information and communication technologies play an important role [4]. The European Commission has started the AAL Programme[1] for funding applied research on AAL technologies. The achieved goals through AAL, as stated by the AAL Programme are:

- to extend the time people are able to live in their preferred environment by increasing their autonomy, self-confidence and mobility;
- to support the preservation of health and functional capabilities of older people;
- to promote better and healthier lifestyles for individuals at risk;
- to increase security, prevent social isolation and create networks of support around elderly people and
- to support carers, families and care organisations.

The AALIANCE2[2] defines the following AAL key scenarios on the basis of interviews with experts [23]: prevention of early degeneration of cognitive abilities, healthy living, management of chronic diseases, age-friendly and safe environments, fall prevention, management of daily activities and keeping control over own life, keeping social contact and having fun, outdoors mobility, avoiding caregivers isolation, and senior citizens at work.

2.3 Fall Detection

Focusing on fall prevention and fall detection, different classes, based on the technology, can be distinguished [41]. Fall detection methods can be classified in wearable devices, robots, audio-based approaches, 2D and 3D sensors [41]. Since this thesis deals with the question, whether image-based devices are intruding on privacy more than other methods, this section is divided in image-based and non-image-based approaches.

[1] `http://www.aal-europe.eu/`, last accessed on 28.08.2019
[2] ALLIANCE2 Consortium, ALLIANCE2 AAL Roadmap 2014, `http://www.aaliance.eu/`, last accessed on 28.08.2019

2.3.1 Non-image-based fall detection methods

Accelerometers are a common tool used for fall detection systems [42, 43, 44]. Beginning in 1991, Lord and Colvin [42] present a triaxial acceleration instrumentation for detecting forces over a defined limit and the duration of the accelerations. A microcomputer chip then makes the information readable on a desktop computer [42].
Williams et al. [43] introduce a fall detection system consisting of a piezoelectric shock sensor and a mercury tilt switch to measure the impact and the orientation of the patient. Despite their low-cost technology and the simple methodology, accelerometer-based wearable devices struggle with high false alarm rates due to physical activities like jumping or post-fall posture [44]. Development in wearable telemedicine technology has made counteracting those problems easier [45].
Wang et al. [44] use three different inertia parameters based on acceleration and angular velocity to improve the selectivity of their fall detection method. The chest-worn sensor reaches a lower rate of misclassifications than methods based on one parameter only [44]. Sabatini et al. [46] analyse the impact and the change of posture using an accelerometer together with a barometric altimeter. By estimating the vertical velocity and the height of the body part the barometric altimeter is attached to, a pre- and post-fall algorithm is applied [46].

Other methods are based on the use of smartphone-included sensors to detect falls and to avoid an additional device that has to be carried around [45]. Kau and Chen [47] propose using the electronical compass and the triaxial accelerometer on the smartphone for detecting falls. With the tilt angle and waveform sequence as inputs, a feature sequence is generated and analysed using a classifier method.
Hakim et al. [48] use the inertial measurement unit with a machine learning algorithm to classify activities of daily living in order to reduce the number of fall alerts. A problem that arises through the use of smartphones as fall sensors is the limitations in battery, memory and real-time processing [49].
Apart from accelerometer-based methods, smartphones can also be used to detect falls by using the integrated microphone [45]. Khan et al. [50] split the audio signals into frames for extracting the frequency spectral features. With a collection of footstep sound signals and the use of a one class support vector machine method, falls are distinguished from non-falls [50]. The difficulties in this method lie in the generation of training data, since realistic fall sound signatures are difficult to design [51]. Moreover, the proper use of acoustic and vibration sensors is restricted to a certain floor type [45].

Pressure sensors are the most common type of ambient sensors [45]. Ambient sensors are not wearable devices but attached to the surrounding area of a person, as for example at home [49]. The low costs and the non-obtrusiveness of pressure sensors are in opposition to the low detection precision, which is below 90% [52].
Passive Infrared (PIR) sensors use infrared signatures to detect falls [45]. As the signal changes with motion of a hot object in front of the sensor, a person can be recognized [53]. Falling and Activities of Daily Living (ADL) like walking can produce similar signals [53].

Hence, Yazar et al. [53] use a combination of PIR and floor vibration for fall detection. For the analysis of signals from the vibration sensors, a feature extraction method based on a single-tree complex wavelet transform is used. The PIR is integrated for reducing the number of false alarms that can occur due to falling objects or slamming doors. A major disadvantage when using PIR sensors is the restricted area where falls can be detected [45].

Doppler sensors can distinguish moving objects from background noise and have the advantage of being cheap as well as small [54]. The drawback of this method is that doppler sensors are less sensitive to movements orthogonal to the irradiation direction than to movements in the irradiation direction [55]. Tomii et al. [55] propose a method using multiple doppler sensors to reduce the dependency on the movement direction. A support vector machine is used to classify the extracted features, which results in 95.5% of accuracy using three sensors [55] . When using doppler sensors for fall detection, the fact that the electrometric wave signals can penetrate apartment walls has to be considered because it limits the usage in a multi-party house [45].

Rimminen et al. [56] develop a near-field imaging system with sensors below the floor. The location and patterns of the user are analysed in order to detect a fall [56]. This method is limited to the area where sensors are placed [56], which leads to increasing costs when expanding this area. Furthermore, pets or occlusions cause false alarms [45].

Velumani and Vijayakumar [57] propose a method to detect falls by analysing the channel state information of different signals generated in the environment of the user with the use of WiFi devices. Changes in the signal concerning phase and amplitude can be used to analyse human activity [57]. The full paper has not been published yet, thus the outcomes cannot be analysed yet.

Toda and Shinomiya [58] use RFID tags attached to shoes to detect falls. The tags transmit the pressure transition from person to ground [58]. By analysing the movement specific sensor codes, falling of a person can be detected [58]. Although the classification of the movements achieve 99%, this method has the drawback of the necessity of wearing shoes and the fact that falling can only be discovered when the person is standing or walking [58]. Tables 2.1 and 2.2 summarize the presented non-image based methods for fall detection with regard to the sensors and algorithms used.

2.3.2 Image-based fall detection methods

While stationary image-based devices can be installed almost everywhere, users might not take wearables with them while sleeping or taking a shower [59]. Getting up at night poses a risk for falling just as well as wet bathroom floors [59]. Additionally, when using stationary devices, the user does not have to remember wearing and recharging them [45, 60, 59]. Image-based methods combining RGB with skeleton points or using depth images allow the usage in day and night condition [59]. Furthermore, image-based methods can monitor more than one person at a time [60]. Computer vision approaches can also more precisely distinguish between falls and ADLs [59].

On the other side, the use of one single camera in a stationary environment can lead to a restriction in perspective [61]. A further issue arising from the use of image-based

Study	Year	Sensors	Wearable	Algorithm	Privacy sensitive data
Lord and Colvin [42]	1991	triaxial accelerometer	yes	G-forces threshold	-
Williams et al. [43]	1998	piezoelectric shock sensor, mercury tilt switch	yes	peak detection, comparing acceleration values and duration	-
Wang et al. [44]	2018	triaxial accelerometer, gyroscope	yes	threshold for acceleration magnitude, acceleration cubic-product-root magnitude and angular velocity cubic-product-root magnitude	-
Sabatini et al. [46]	2016	inertial and barometric altimeter	yes	two-stage decisional scheme based on velocity, height and posture	-
Kau and Chen [47]	2015	electronic compass and triaxial accelerometer of smartphone	yes	cascaded classifier with a support vector machine	-
Hakim et al. [48]	2016	intertial measurement unit of smartphone	yes	Support Vector Machines, Decision Trees, Nearest Neighbour Classifieres and Discriminant Analysis	-
Khan et al.[50]	2014	2 microphones	no	one-class support vector machine method	audio data
Yazar et al. [53]	2012	vibration and passive infrared sensors	no	single-tree complex wavelet transform for feature extraction, Euclidean distance, Mahalanobis distance and support vector machine classifiers	location and activity data

Table 2.1: Summary of non-image-based fall sensors studies I

Study	Year	Sensors	Wearable	Algorithm	Privacy sensitive data
Tomii et al. [55]	2012	multiple doppler sensors	no	feature combination method, support vector machine and k-nearest neighbour	location data
Rimminen et al. [56]	2010	electric near field floor sensor	no	feature extraction based on number of observations, longest dimension and sum of magnitudes.	location data
Velumani and Vijayakumar [57]	-	carrier state information signal from Wi-Fi devices	no	waveform analysis by use of a support vector machine	activity data
Toda and Shinomiya [58]	2018	RFID tags with sensing capabilities	yes	multiclass decision forest algorithm	-

Table 2.2: Summary of non-image-based fall sensors studies II

methods is the aspect of privacy [62]. RGB cameras are distinguished from depth cameras and infrared sensors [45]. Processing RGB images within the system, sending warning signals instead of pictures [59], using depth images [63] or algorithms for hiding people's identities [60] are approaches to assure privacy.

A common image-based approach for fall detection is to train algorithms with large datasets, so that certain features are recognized and classified [61, 63]. Algorithms are based on the analysis of shape, inactivity or head motion [61]. Fan et al. [61] extract the human body using a background subtraction method. Six different shape features are measured to classify the human posture. A classification vector based on the squared first order temporal derivatives of the created slow features is generated. The research team uses a support vector machine to distinguish falls from other activities. Another method presented by ShanShan et al. [64] is the Gaussian Mixed Model method to extract the human silhouette. Using semi-contour distances, the posture is quantified and classified by a support vector machine technique.

Both Fan et al. [61] and ShanShan et al. [64] extract a person's silhouette from RGB video sequences. Once extracted, only the shape of the human and not his identity is visible. Another approach is the utilization of a depth camera with the purpose of applying privacy protection at the earliest stage. Planinc and Kampel [65] use the Kinect as 3D depth sensor in order to calculate the orientation of different body parts. With the

use of the least square algorithm a straight line is fitted to the data points. Together with the floor orientation and the distance between the spine and the floor, a fall is differed from non-falls.
Zhao et al. [63] focus on falls from bed and use a human upper body extraction method to make the algorithm work even when human-bed interactions happen. The Large Margin Nearest Neighbour classification method is used to detect a fall from the bed. The algorithm is implemented on depth image data, using the Microsoft Kinect and the Orbbec Astra camera. The research team highlights the advantage of depth cameras to be insensitive to illumination variation [63].
A system based on the Kinect sensor and fast Fourier transformation is presented by Kong and Meng [66]. At first, the received RGB and depth image from the sensor is transformed into a skeleton image. By using fast Fourier transformation, the image is then encrypted and sent via a carrier image, which has to be decoded. In order to detect a fall, machine learning is applied. When a person is detected by the sensor, the height and width of the created skeleton image are calculated. These parameters are the basis for the classification which is done with a k-Nearest-Neighbour/Support Vector Machine approach.
Ma et al. [60] present a method using a thermal camera to determine and to extract facial regions. Visible light rays enter, controlled by a Spatial Light Modulator (SLM), an RGB camera, where only images with hidden facial regions are processed. In order to detect falls, this method combines a 3D convolutional neural network with an autoencoder. While the neural network is used for feature extraction, the autoencoder models normal behaviour. A method presented by Kido et al. [67] uses solely a thermal camera to detect falls in bathroom environments. Normal activities in the toilet room are distinguished from falls by performing discriminant analysis. Therefore, the thermal image is split into 81 areas with known average temperature. One disadvantage of this method is that it requires visual confirming by caregivers [67] .
Ozcan and Velipasalar [62] propose a computer vision approach, that is not restricted to a specific location. Instead, a wearable camera is used to ensure the detection of falls independent of the environment [62]. Histograms of Oriented Gradients are combined with Gradient Local Binary Patterns to generate features. The classification of fall events is implemented by using a relative-entropy-based method. Table 2.3 summarizes the presented image-based fall detection methods.

2.4 Fall Prevention

A part of fall prevention deals with recognizing balance and motion abnormalities to assess the fall risk of a person [68]. Another approach is to detect a person leaving the bed without assistance and sending alarms to the care givers for helping the person [69]. In the following work, the event of a person getting up from bed is referred to as “getup event” or “getup”.

Study	Year	Sensors	Wearable	Algorithm	Privacy sensitive data
Fan et al. [61]	2018	RGB camera	no	background subtraction, classification vector based on slow features	RGB images
ShanShan et al. [64]	2018	RGB camera	no	Gaussian Mixed Model, support vector machine classification	RGB images
Planinc et al. [65]	2013	3D depth sensor	no	feature extraction by use of similarity to the ground orientation and the height	depth data
Zhao et al. [63]	2018	3D depth sensor	no	human upper body extraction method, Large Margin Nearest Neighbour classification	depth data
Kong and Meng [66]	2018	RGBD camera	no	machine learning approach based on height and width of skeleton images	RGB and depth data
Ma et al. [60]	2019	RGB and infrared camera	no	combination of 3D convolutional neural network and an autoencoder	RGB and infrared images
Kido et al. [67]	2009	infrared camera	no	discriminant analysis	infrared images
Ozcan and Velipasalar [62]	2017	RGB camera	yes	relative-entropy-based classification method, Histograms of Oriented Gradients are combined with Gradient Local Binary Patterns to generate features	RGB images

Table 2.3: Summary of image-based fall sensors studies

2.4.1 Non-image-based fall prevention

A method to prevent patients falling from bed are restraints such as bed rails [70]. But when applying restraints, the risk of injury has been found to increase [71]. Beds mounted close to the ground as well as floor mats in front of the bed are one of the solutions developed to prevent falls and to minimize the extent of injury [69]. A drawback of those devices is that they cannot alarm nursing staff [19]. Although pressure-sensitive mats (see Figure 2.3) with the functionality of sending alarms when the pressure exceeds a certain threshold exist [72, 73], they can pose a risk for tripping [74].

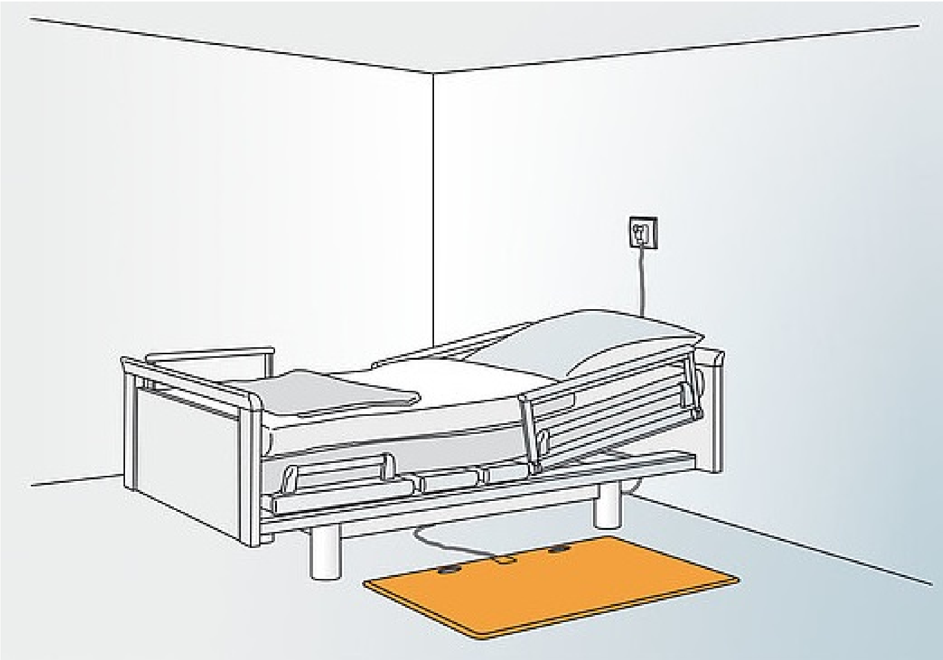

Figure 2.3: Pressure-sensitive mat in front of the bed[3].

Hilbe et al. [69] present a pressure-based device called *Bucinator* (see Image 2.4) to eliminate those drawbacks. The device mounted under the mattress alarms health workers when patients are leaving the bed. Rails filled with air are connected with a pressure sensor, which generates an electrical alarm when exceeding a pre-defined threshold.

In general, one can group fall prevention systems into those that detect a person in danger of falling (in the following called direct fall prevention approaches) and those that help to improve a persons balance and strength (in the following called indirect approaches) [10]. One example of an indirect approach is a robot developed by Maneeprom et al. [75]. The robot shows videos about how to prevent falls, giving advice on choosing

[3] Image from `https://smartaccess.bircher.com/sensoren-und-schalter-von-bbc-bircher-smart-access-weltweite-lieferung/sicherheitsschaltmatte-caremat-sicherheit-und-entlastung-im-pflegebereich/`, last accessed on 28.08.2019

Figure 2.4: Bucinator Paulus

appropriate shoes and walking assistive devices. Additionally, daily voice messages and exercise reminders are provided.
The direct approaches can be divided into two subgroups. On the one hand, there are assessment tests, which classify a person's risk of fall based on balance and mobility tests [68]. A method developed by Yamada et al. [76] uses the Wii Fit's "Ski Slalom" and "Basic Step" games to assess the fall risk of elderly people. Comparing the results with five different tests like the Timed Up & Go (TUG) under single- and dual-task condition, the "Basic Step" game shows a significant difference between fallers and nonfallers [76]. The TUG is a commonly used method to assess the risk of a person falling by determining the time a person needs for standing up from a chair, walking three metres and returning to sit on the chair again [76, 77].
On the other hand, there are devices like the Bucinator which alarm health staff in case of an urgent risk of falling, analysing the person's posture, balance or pressure on a sensor [69].
Lee et al. [78] use ten piezoresistive pressure sensor pads positioned in a bed mattress to measure the pressure applied on the sensors. By evaluating the pressure values, a person's position and activity status is determined. When a person is about to exit the bed, an alarm is sent via a mobile application.
A method based on a body-worn accelerometer is presented by Wolf et al. [79]. An accelerometer positioned with a tape on the user's leg calculates the orientation of the sensor and the amount of movement to distinguish between lying, sitting and standing. Ribeiro et al. [80] develop a mat consisting of a pressure sensor and a 3-axial accelerometer to detect movements on the bed or armchair. A control system analyses arm as well as torso movements to detect a person getting up from bed or from a chair. A warning level loop with different states is used to offer the opportunity to manually deactivate a visual warning light before sending an acoustic alarm. Table 2.4 summarizes the presented non-image-based methods for fall prevention.

2.4.2 Image-based fall prevention

Not only in fall detection, but also in fall prevention, image-based sensors like RGB or depth cameras do play a role [81]. They are used to measure balance, stability, reaction time, diversions from typical activity patterns and other physical parameters [10, 74]. Moreover, they are used for games and activities operated via a camera with the intention to improve a person's balance and strength [81].

Study	Year	Wearable	Principle	Privacy sensitive data
Hilbe et al. [69]	2009	no	pressure-sensitive device mounted under the mattress, alarm when exceeding threshold	bed exit
Maneeprom et al. [75]	2019	no	robot providing videos and audio messages to prevent falls	-
Yamada et al. [76]	2011	no	Wii Fit games for fall risk assessment	-
Lee et al. [78]	2018	no	pressure sensor pads in the mattress	bed exit
Wolf et al. [79]	2013	yes	body-worn accelerometer	bed exit
Ribeiro et al. [80]	2018	no	pressure sensor and 3-axial accelerometer	bed exit

Table 2.4: Summary of non-image-based fall prevention studies

A product commonly used as a tool to assess the fall risk of elderly is the *Kinect* sensor from Microsoft [68, 77, 82]. Kampel et al. [77] use the Kinect to automatically analyse the TUG. Two different approaches to calculate the start and end time of six TUG phases are presented. When working with skeleton data, the trajectory of the spine-shoulder joint is used for the computation, while it is the center of mass of a person when using depth data.
Dubois et al. [68] present a method to automatically evaluate a person's risk of falling by carrying out eight different balance tasks in front of the Kinect. In order to assess the stability during a task, the body centroid is calculated. The horizontal dispersion of the pixel cloud is used to determine whether a person uses the arms to maintain the balance. For the final assessment of the individual fall risk, apart from the balance tasks, the age, average physical activity and results from the TUG are considered too.
Rantz et al. [82] use the Kinect to design a system for the home-environment of elderly people in order to continuously analyse gate parameters like velocity, step and stride length. The use of automatic gait assessment methods has the advantage of a regular tracking of fall risk parameters [82]. In case of an increased risk, nursing staff can be alerted. By including a doppler radar, the problem of occlusion is avoided. Similar to the previously described bed exit alarm system Bucinator, cameras are also used to inform health workers when a patient with an increased risk of falling is about to leave the bed [83, 19].
Ni et al. [83] combine the Kinect's depth sensor with its RGB camera to monitor patients and to alert the nursing staff in case of need. The region around the bed is defined as

region of interest and split into eight rectangular blocks. Multiple motion and shape features are extracted and combined using a multiple kernel learning framework.
The system *Ocuvera*, developed by Bauer et al. [19] uses the Kinect's depth sensor only. After detecting the floor and the bed, machine-learned shape models are used to find human shapes. For every person found in the scene the likelihood of bed exit is predicited in order to trigger alarms before a person exits the bed. Problems that still need to be addressed are the integration in existing alarm technology of hospitals and the improvement of the algorithm in order minimize the time between the event and the alarm [19]. Table 2.5 summarizes the presented image-based methods for fall prevention.

Study	Year	Sensors	Wearable	Parameters	Privacy sensitive data
Kampel et al. [77]	2018	3D depth sensor	no	trajectory of the spine-shoulder joint, center of mass	depth data
Dubois et al. [68]	2019	3D depth sensor	no	body centroid and dispersion depth data	depth data
Rantz et al. [82]	2015	3D depth sensor, 2 web cameras, doppler radar	no	velocity, step length, and stride length	depth data
Ni et al. [83]	2012	RGBD camera	no	motion and shape features including motion history images, histogram of optic flows and histogram of oriented gradients	RGB and depth data
Bauer et al. [19]	2017	3D depth sensor	no	machine-learned shape models	depth data

Table 2.5: Summary of image-based fall prevention studies

2.5 Dealing with privacy

While developing new AAL devices, ethical topics have to be considered to ensure user acceptance [23]. The AALIANCE2 Consortium describes privacy protection, social isolation, abuse and consent as the four key issues concerning ethics in AAL (see Image 2.5)

[23]. If not otherwise declared, the following description of these key points is based on the Ambient assisted living roadmap published by the AALIANCE2 Consortium [23].

Social isolation
The demand for new AAL technology is to not replace human contact. Especially the group of elderly people has a higher risk of social isolation, depending on the geographical and social situation. Although AAL devices can lead to a more autonomous life, the fear of social isolation by reducing human contact exists.

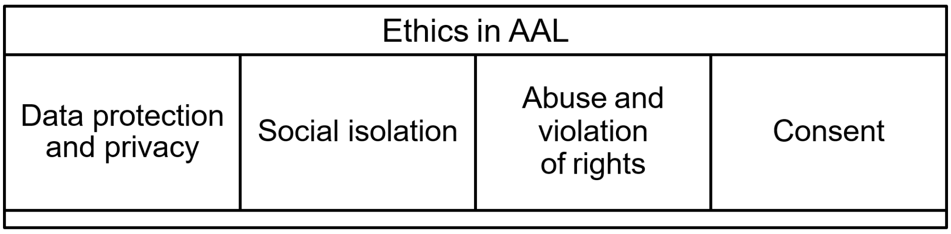

Figure 2.5: Key issues regarding ethics in AAL.

Abuse and violation of rights
The World Health Organization defines abuse as “a single or repeated act or lack of appropriate action, occurring within any relationship in which there is an expectation of trust, that causes harm or distress to older people” [84].

The expectation of trust does play a role when speaking of abuse by increasing when a person is in need of care. Examples for abusive situations in AAL are financial abuse by companies selling these products or control from the family over the private life of an older relative. In order to avoid abuse of elderly people, offering trial periods and the possibility to demount the device at any time as well as training professionals and the regular assessment of the impact of AAL is advised.

Consent
Consent is a key element in respecting an individual’s dignity and freedom. The aim of consent is an understanding of the planned treatment with a continuous communication being required [85]. When installing AAL devices in the home of elderly people, the following questions occur: how is the consent given, and what if the person is unable to give consent. Generally, an informed consent shall be given in written form. Additionally, recording a person’s status and presenting exit strategies are advised. Especially for people diagnosed with dementia regular assessment is required to gain information about the impact of AAL on the person’s quality of life.

Data protection and privacy
When providing AAL devices, a transparent process of collecting and analysing data is required and (in Europe) regulated by the EU General Data Protection Regulation

(GDPR)[4]. How, where, how long and by whom data is stored and processed shall be included into contracts and consent forms. Different options to protect a person's privacy shall be provided to consider data protection according to a person's wishes.

Especially when using image-based technology, concerns of privacy are raised [16]. Lord and Colvin [42] present a simple RGB video monitoring system for fall detection in combination with an accelerometer. While the outcome is promising, the acceptance of the system is not given due to privacy issues [42]. On the other side, several research teams developing image-based approaches for fall detection and prevention know about that issue and evolve solutions according to that [63, 60]. The use of depth cameras enables the application of privacy protection at an early stage since depth images only contain information relating to the distance of the surfaces of scene objects from a viewpoint and cannot directly identify a person [63, 86].
Ma et al. [60] do not use depth images, but use a thermal camera in order to hide facial regions. In a first step, facial regions are located via the thermal camera. This is privacy-safe because no person can be identified via a thermal image [67, 87]. The reason for that is the similar facial temperature distributions of human faces [88]. Thus, faces in thermal images cannot be distinguished from each other [88]. For the detected facial regions mask patterns are created, which are then displayed on an SLM. The SLM controls the light rays entering the RGB image sensor. It blocks the visible light rays from facial regions. Thus, light rays from people's faces cannot enter the RGB image sensor. Instead, facial regions appear black. The light rays from the scene can enter the thermal image sensor and the RGB image sensor at the same time using a cold mirror[5]. The mirror sends infrared rays to the thermal image sensor and reflects the visible light rays via the SLM to the RGB image sensor. This process repeats while the fall detection algorithm is running and delivers only anonymous video output. With the use of pre-processing methods, meaning methods altering RGB images at the image capturing stage, it is possible to overcome the drawbacks of having a vulnerable time of privacy leakage before hiding facial regions [60]. The disadvantage of this method is that the privacy protection approach depends on the accuracy of the face detection algorithm [60, 16]. The method of Kido et al. [67] bypasses this problem by solely using an infrared camera. If the privacy detection approach is applied at a later stage or if wireless communication is included, encryption and data security methods must be applied [89].
The wearable RGB camera presented by Ozcan and Velipasalar [62] does not take images of the subject, but from the environment. Although the images are only processed locally and are not stored [62], this method raises privacy issues for bystanders [90]. Sabatini et al. [46] state that wearable sensors do not raise any privacy issues, but devices using GPS or audio data can be intrusive as well [91]. Khan et al. [50] use an audio based approach and argue that via an active microphone, the privacy issue is reduced in comparison with image-based approaches. In Table 2.1-2.5 the presented image-based and non-image-based methods for fall prevention and fall detection are summarized, also

[4] `https://eugdpr.org/`, last accessed on 28.08.2019

[5] A cold mirror is a dichroic filter that absorbs about 80% of infrared rays and reflects all visible light rays [60].

specifying privacy-sensitive data processed within this approach.

In how far the intervention in one's privacy differs between methods cannot be stated due to a non-uniform definition of obtrusiveness [92]. In 2006, Hensel et al. [93] provide a definition for obtrusiveness. They state that obtrusiveness is a "summary evaluation by the user based on characteristics or effects associated with the technology that are perceived as undesirable and physically and/or psychologically prominent" [93]. Introducing different categories and dimensions of obtrusiveness, a first move towards a measurement for obtrusiveness is done [93]. Still being the most complete framework in this field twelve years later [92], Blasco et al. [92] adopt Hensel and colleagues' work for their application area. Both Hensel et al. [93] and Blasco et al. [92] emphasize the subjectivity of obtrusiveness. Different users might not feel invaded in their privacy by the same technology [93, 92].

2.6 User Acceptance Models

Although new technologies in AAL are developed, they still do not play a main part in people's lives [20]. The acceptance of technology by the user plays a role in this context [20, 94]. Models have been established and applied to specific fields in order to understand the factors that influence the acceptance of technologies [94].

2.6.1 Technology Acceptance Model

The Technology Acceptance Model (TAM) was designed in 1986 by Davis specifically to predict people's intention to use Information Systems (IS) [95]. The TAM can be seen in Figure 2.6 and is based on the theory that the intention of a person to use a system is determined by two factors: the Perceived Usefulness (PU) and the Perceived Ease of Use (PEoU) [96]. PU is defined as the extent to which one believes that a system will improve one's job performance [96]. PEoU means the degree to which one believes that using the system will be free of effort [96]. The overall Attitude Towards Using (ATU) is assumed to be directly linked to the actual usage.

Conversely, PU and PEoU contribute to the ATU [96]. Figure 2.6 also shows that PEoU has a causal effect on PU [97]. This can be explained by saying that a system that is easier to use will result in increased job performance for the user [97]. External variables (the design features) contribute to PU and PEoU. Davis follows the theory of Fishbein [98] that the relationships in the model are linear. The calculation of PEoU, PU, ATU and the Actual Use of the System (USE) can be seen in Equation 2.1-2.4 (from [97]).

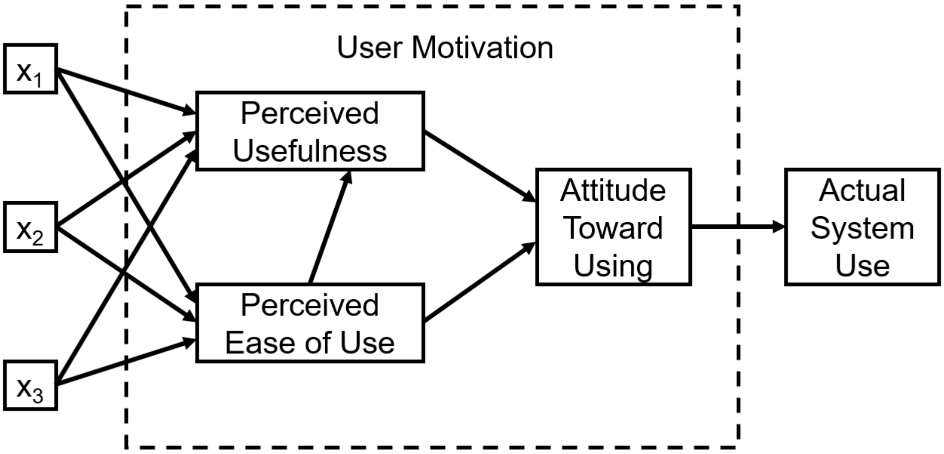

Figure 2.6: TAM developed by Davis in 1986. (Image from [97])

$$\mathrm{PEoU} = \sum_{i=1}^{n} \beta_{\mathrm{i}} X_{\mathrm{i}} + \varepsilon \tag{2.1}$$

$$\mathrm{PU} = \sum_{i=1}^{n} \beta_{\mathrm{i}} X_{\mathrm{i}} + \beta_{\mathrm{n+1}} \mathrm{PEoU} + \varepsilon \tag{2.2}$$

$$\mathrm{ATU} = \beta_1 \mathrm{PEoU} + \beta_2 \mathrm{PU} + \varepsilon \tag{2.3}$$

$$\mathrm{USE} = \beta_1 \mathrm{ATT} + \varepsilon \tag{2.4}$$

with:

$$X_{\mathrm{i}} = design\ feature\ i,\ \ i = 1, n$$
$$\beta_{\mathrm{i}} = standardized\ partial\ regression\ coefficient$$
$$\varepsilon = random\ error\ term$$

Venkatesh and Davis extend their model in order to better understand the two main factors PEoU and PU [99, 96]. The determinants for those two factors as well as their change with increasing user experience over time with a certain system are analysed [96]. This results in the TAM2, which includes additional factors such as social influences and cognitive instrumental processes (see Figure 2.7) [96].

Davis and Venkatesh describe the new factors as following [96]: Subjective Norm is the influence of people close to someone to perform or not perform a certain behaviour. Image is connected to the Subjective Norm and characterizes the perception of a person that a certain behaviour raises one's status in one's social system. Job Relevance describes how a person believes the target system is applicable to his job. Output Quality means how well the target system performs its tasks. Result Demonstrability is specified as the ability of a person to comprehend the result of using the system. Voluntariness describes

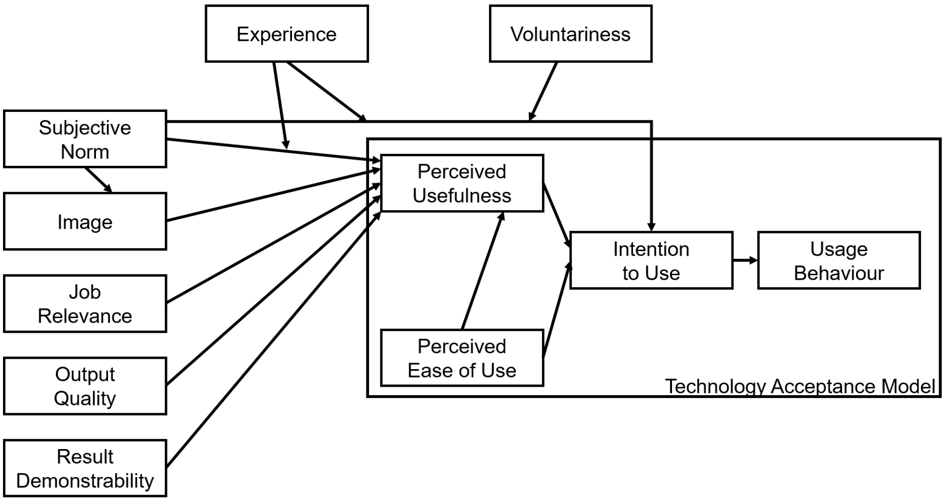

Figure 2.7: TAM2 developed by Venkatesh and Davis in 2000. (Image from [96])

the perception of a person that his decision to adopt to a system is non-mandatory. Experience means the experience with a certain system.
Four longitudinal field studies are carried out to test TAM2. It is shown that Subjective Norm has a significant direct effect on usage intentions [96]. For mandatory, but not for voluntary systems, this effect is even bigger than PU and PEoU have on the use of a system [96]. Social influences are not found when a system is used voluntarily [96, 97]. The influence of Subjective Norm on PEoU is confirmed [96]. Another finding is that if one's job goals and the system's job relevance match, this leads to a higher PU [96]. The hypothesis that user perception of result demonstration and ease of use are significant is verified [96].

2.6.2 Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) developed by Ajzen in 1985 deals with the prediction of human's behaviour [95]. The behaviour is determined by the Intention (In) to perform that behaviour, which is predicted by Attitude towards the Behaviour (AtB), Subjective Norms (SN) and Perceived Behavioural Control (PBC) [95]. AtB and In are equally defined in TPB and in TAM [95, 96]. While SN describes the individual's perception of social pressure to perform a certain behaviour, PBC characterizes the belief of a person in having control over the performance of the behaviour [95]. A schematic overview of the TPB can be seen in Figure 2.8.

Although the TPB model is unspecific in its application, it can be converted to the use of IS [95]. TPB and TAM are compared by Mathieson [95]. Both models are suitable for predicting the intention to use IS, although TAM has a slight empirical advantage [95]. TAM explains ATU in context of IS better than TPB, which speaks for using TAM when examining this variable [95]. TAM has the advantage of an easier application than TPB,

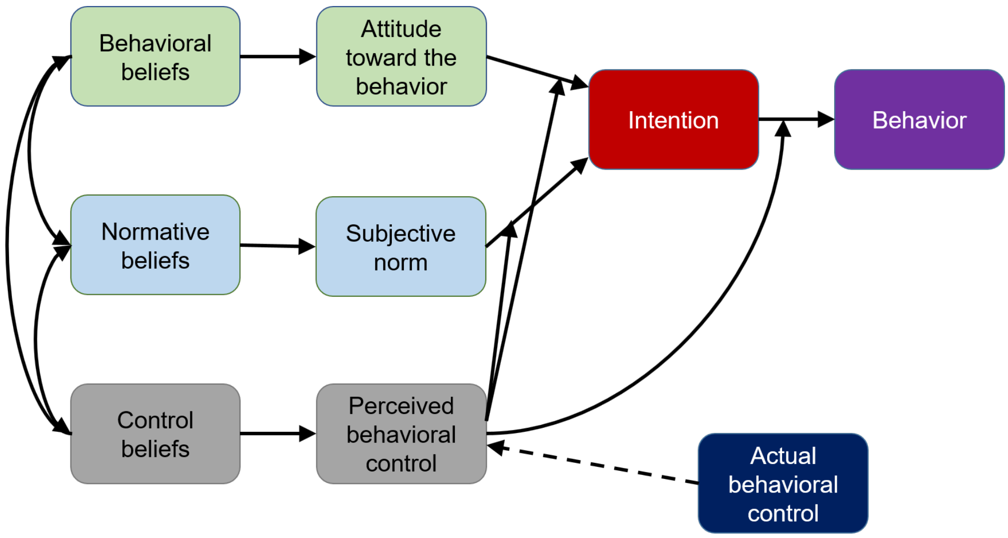

Figure 2.8: Theory of Planned Behaviour[6].

but is also more general in the description of ease of use and usefulness [95]. The TPB delivers more specific information which has the advantage of better directing development [95]. Sun et al. [99] empirically compare different acceptance models in the context of mobile health services. They show that the UTAUT outperforms the TAM as well as the TPB [99].

2.6.3 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) model was initially created by Venkatesh [100] in 2003. This is another extension of the TAM2 model, which is based on the comparison of prominent models at that time [99]. The terms PEoU, PU and SN are represented by the new terms Performance Expectancy (PE), Effort Expectancy (EE) and Social Influence (SI) [99]. The terms are described as following [100]: PE describes how an individual believes that using a system will increase his job performance. EE is specified as the degree of ease associated with the use of the system [100]. SI depicts the degree to which an individual perceives that important others believe he or she should use the new system [100]. In UTAUT, the factor Facilitating Conditions (FC) is additionally introduced [100]. FC describes the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system [100].
The Intention to Use and Usage Behaviour are relabeled to Behavioural Intention (BI) and Use Behaviour. Venkatesh et al. [101] extend the UTAUT model to UTAUT2 adding three factors: Hedonic Motivation (HM), Price Value (PV) and Experience and Habit (EH) (see Figure 2.9). The factors are defined as following [101]: HM means fun or pleasure

[6] Image from http://people.umass.edu/aizen/tpb.diag.html, last search: 12.08.2019)

derived from using a technology. PV is defined as the consumers' cognitive tradeoff between perceived benefits and the monetary cost for using the product. EH: Experience is the opportunity to use a technology, for a certain time, while Habit describes the extent to which people tend to perform behaviours automatically because of learning. These factors are confirmed to influence technology use [101]. The study carried out by Venkatesh et al. [101] is fitted in the context of consumer acceptance. HM is found to influence BI by age, gender and experience [101]. PV affects BI by age and gender [101]. EH has direct and mediated effects on technology use [101].

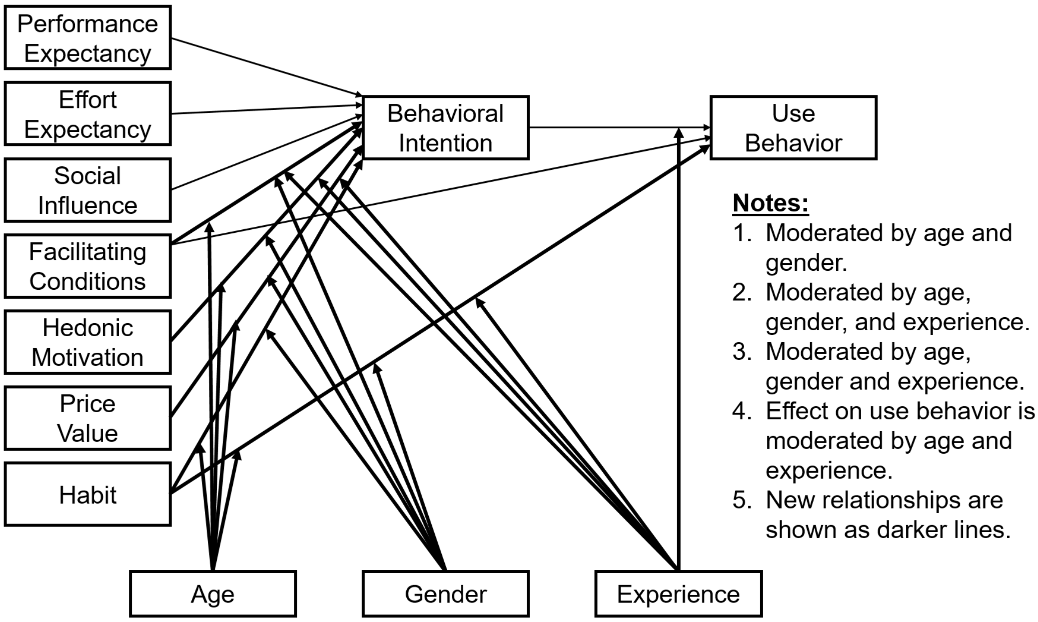

Figure 2.9: UTAUT2 developed by Venkatesh et al. (Image from [101])

Halbach et al. [20] adapt the UTAUT2 model for the use in AAL with a special focus on user diversity (age, gender, ATT, health status, caregiving experience) because the user itself causes a lot of variance [102, 103]. They carry out a prestudy with two different age groups (Group 1: 5 people with mean age 24.4, Group 2: 7 people with mean age 60.7) [20]. After demonstrating four different AAL systems, the groups are asked to discuss them. A camera-based system for fall detection is rejected in both groups. An acceptable solution for protecting user's privacy is the infrared sensor. As the privacy issue was present in the discussion, Halbach and colleagues [20] add the construct Privacy Concerns (PC) to their model [20]. The second added construct is Design and Integration (DI). DI is the perception of the system in visual aspects [20]. The construct PV is not used as the scenario in the study was only an example and shows an unacceptable reliability score of $\alpha = 0.451$ [20]. SI and FC show values above $\alpha = 0.5$, while all other dimensions gain high reliability scores (above $\alpha = 0.8$) [20]. Halbach et al. [20] conclude that gender and health status are irrelevant for AAL acceptance, while age, ATT and caregiving experience do play a role in this context.

CHAPTER 3

Methodology

In order to compare devices for fall prevention and fall detection, an approach to measure their performance is developed. The sensitivity and precision are calculated from data derived from laboratory and field tests. The data delivers information about the alarm behaviour of the devices and their temporal alignment to the actual getup, fall or ADL. Based on the adapted UTAUT2 model from Halbach et al. [20], a questionnaire is created to analyse the user acceptance of AAL technology, with a focus on fall prevention and fall detection systems.

3.1 Fall Preventive Systems

For evaluating different products for fall prevention, a field study with a run-time of 28 days is carried out in a cooperating care home in Salzburg. Four people participate in the study. Occurring getup events are collected and compared with the alarm behaviour of the tested devices.

3.1.1 Products for comparison

As this study aims at analysing the current market situation in the field of fall prevention and fall detection, products for the B2B as well as the B2C market are considered. Table 3.1 shows the devices found on the basis of a web research. A major criterion for the chosen products is the integration into the facilities of the care home without influencing everyday life for patients and staff. Considering as well the representation of the product categories found via the web search (pressure-, image- and motion-based technologies) results in the following products:

- *Bucinator*
  The pressure-based system is placed below the mattress of the resident. When a

Product	Company	Product	Company	Product	Company
Bucinator Vivus	Bucinator	Bucinator Paulus	Bucinator	BedGuard	Vontech Medizintechnik & Service
SafePAD	Serobac	SafeBED	Serobac	SafeFLOOR	Serobac
Sensoria	Sensoria Inc.	Oxehealth	Oxehealth	Optiscan	distributed by Rehatronik GmbH
CareMat	distributed by Rehatronik GmbH	Grannyguard	Pikkerton GmbH	fearless, the intelligent fall sensor	cogvis software und consulting GmbH
Optex EX-35R	WinkerTec				

Table 3.1: Fall prevention devices on the market

person is getting up from bed, an alarm is sent via a wireless transmitter. Rails filled with air are connected with a pressure sensor, which generates an electrical alarm when exceeding a pre-defined threshold [69]. Two different products can be distinguished: the *Bucinator Paulus* (see Image 2.4 and Image 3.1), which is laid laterally below the mattress. It sends an alarm whenever the pressure on the sensor exceeds a certain threshold. The *Bucinator Vivus* (see Image 3.2) is placed crosswise under the mattress and is activated when a person is lying in bed. When the person gets up from bed and the pressure is relieved from the sensor, an alarm is sent. Furthermore, the Bucinator Vivus has a control unit with two options: either the alarm is sent when a person leaves the bed, or when the person does not return within 15 minutes.

- *Fearless, the intelligent fall sensor* (in the following work also called "fearless sensor" or "fearless") from Cogvis and Consulting GmbH:
  The image-based sensor (see Image 3.3) is based on the work of Planinc and Kampel [65] and combines getup and fall detection. The system detects a person getting up from bed by analysing depth data. When a getup event occurs, an alarm is sent via wireless communication, SMS or e-mail. Depending on the settings on the web platform, the alarm can be sent either when a person is raising up in bed, when sitting on the edge of the bed or when standing up.

Figure 3.1: Illustration of the bed exit alarm system Bucinator Paulus[7].

Figure 3.2: Bucinator Vivus[8]

Figure 3.3: Fearless[9]

- Motion sensor *Optex EX-35R* (in the following work named "Optex" or "Optex sensor") from WinkerTec:
  The motion sensor (see Figure 3.4) is placed besides the bed (e.g. on the wall). An alarm is transmitted via radio signals when a motion is detected. The angle of the sensor can be adjusted depending on its positioning: the wide-angle setting is applied for doors, while the long-distance setting is used for the application next to the bed. The sensor is only active when it has not registered any motion in the previous two minutes in order to avoid multiple alarms for a single event.

[7] Image from http://www.bucinator.at/, last accessed on 28.08.2019
[8] Image from https://www.kuhnbieri.ch/de/alarmsystem-bucinator-mit-eldat-funksender-4.html, last accessed on 28.08.2019
[9] Image from https://www.cogvis.at/, last accessed on 28.08.2019

Figure 3.4: Motion sensor *Optex EX-35r* from WinkerTec[10].

3.1.2 Comparison approach

A common method to describe the performance of fall detection systems is the computation of the sensitivity and specificity [16, 104]. A device can either detect an event or it does not. Thus, the output is binary. Four different cases are possible [16]:

- True Positive (TP): an event occurs and it is detected properly
- False Positive (FP): an event is detected although it did not occur
- True Negative (TN): no event occurs and the system does not detect one
- False Negative (FN): an event occurs but the system does not detect it

Noury et al. [16] propose a statistical analysis on a series of tests, evaluating the results by means of sensitivity and specificity.

Sensitivity describes the capacity to detect an event [16]:

$$Sensitivity = \frac{\text{TP}}{\text{TP+FN}}$$

Specificity describes the capacity to detect only the target event [16]:

$$Specificity = \frac{\text{TN}}{\text{TN+FP}}$$

The TNs cannot be calculated because of an infinite number of ADLs. Thus, the sensitivity (also called recall) and precision are calculated as metrics for the product's performances. The precision is given as

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$$

and describes how many false alarms occur and thus, how useful the search results are [45].

In order to determine whether a getup event has occurred or not, a motion-based recording, provided by Cogvis and Consulting GmbH is used. Therefore a hard disk is connected to the fearless sensor. For each of the four participants the three products, two radio receivers from *ELDAT GmbH* (in the following called Eldat receiver), a hard disk and a *Raspberry Pi B3* (in the following called Raspberry) are placed in the participants' rooms. Two participants are equipped with the Bucinator Paulus and the other two with the Bucinator Vivus.

All three products use radio communication for sending alarms and are compatible with Eldat. Thus, Eldat receivers are used to gain information about when each product sends an alarm. For this reason, a the Raspberry is connected to two receivers, one for the Bucinator and one for the Optex sensor. Since the fearless web platform[11] provides information about all incoming alarms, a third receiver is not required. Image 3.5 shows the Raspberry-Eldat construction. Each Eldat receiver is trained for the corresponding product. Via a Python script running on the Raspberry, a timestamp is written in a textfile each time a signal is arriving. Only one alarm per five minutes is accepted to avoid duplicate alarms for the same event.

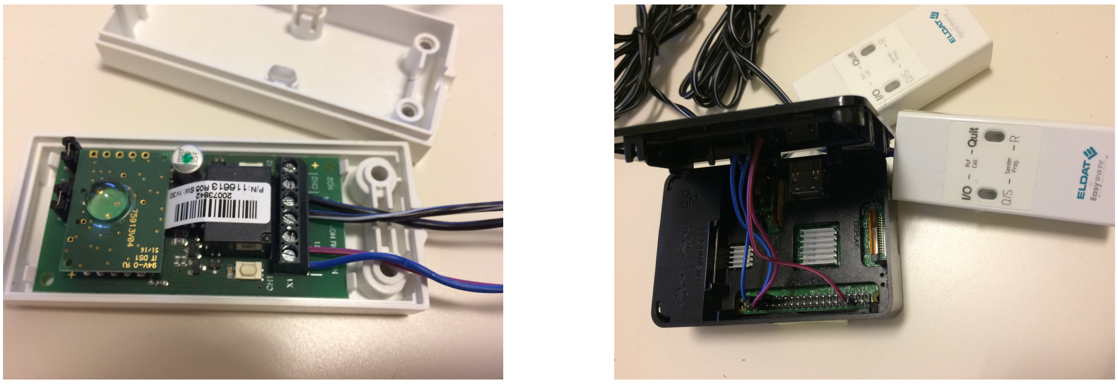

Figure 3.5: Data collecting construction consisting of a Raspberry Pi and Eldat receivers.

10 Image from https://winkertec.de/produkt/infrarotmelder/, last accessed on 28.08.2019

11 https://web.fearless-system.com/#!/login, last accessed on 28.08.2019

After one month of collecting data, the recording is evaluated. Therefore, the depth image sequences are analysed. The time stamp of every getup event seen in the sequences is extracted and used as a basis for verifying or falsifying the alarms sent by a device. For doing so, the getup event itself is defined as the moment when the person starts to lift his posterior from the bed while stretching his legs and/or pushing his hands against the bed.
The event is verified when the time of the alarm is sent either within two minutes before or one minute after the actual event. The result of this analysis is a pool of binary data consisting of "alarmed" or "not alarmed". From that data, the recall and precision can be calculated to analyse the performance for the different devices.

3.1.3 Setting

The fall prevention devices are installed in four different rooms in a care home in Salzburg, Austria. All of the rooms are single occupancy rooms and provided with a 90x200 cm bed. Table 3.2 points out the age, sex, weight and height of the residents, while Table 3.3 shows the devices' positions. All weights are given in kilograms and all distances in metres. While the position of both Optex and the fearless sensor have to be adjusted to the given environment, all of the Bucinator devices can be positioned using the same distances. Figure 3.6 illustrates the distances given in Table 3.3.

Room #	**Age**	**Gender**	**Weight [kg]**	**Height [m]**
1	95	female	58.4	1.50
2	93	female	42.2	1.55
3	93	female	55.0	1.60
4	89	female	73.9	1.57

Table 3.2: Statistics of participants in fall prevention study

	Fearless			**Optex**		**Bucinator**	
						Paulus	**Vivus**
Room #	$\overline{BC}$ **[m]**	$\overline{AB}$ **[m]**	$\overline{AC}$ **[m]**	$\overline{EF}$ **[m]**	$\overline{DE}$ **[m]**	$\overline{GH}$ **[m]**	$\overline{IJ}$ **[m]**
1	2.60	2.30	3.47	0.30	0.55	0.90	0.90
2	4.60	2.95	5.47	0.70	0.60	0.90	0.90
3	2.90	3.10	4.25	0.20	0.45	0.90	0.90
4	2.40	2.30	3.32	0.40	0.60	0.90	0.90

Table 3.3: Device positioning data of fall prevention study

According to the instruction manual, the Bucinator Paulus is positioned laterally under the mattress, and the Bucinator Vivus is placed crosswise in the breast or back region. More detailed information is not given, thus both products are placed 90 cm away from the top of the bed (see Figure 3.6). Although in one room, either the Bucinator Paulus or the Bucinator Vivus is used, Figure 3.6 shows both to demonstrate the ideal position of the devices in one image.
For the Optex sensor, the distance $\overline{DE}$ shall be between 30 and 90 cm and $\overline{EF}$ shall be between 20-40 cm. In room 1, 3 and 4, these criteria are met (see Table 3.3). In room number 2, a bedside table, which should not be moved, precludes the positioning withing the given length. The low installation height also makes it easier to block the sensor with different objects. These factors are considered when evaluating the results.
The fearless sensor has a maximal range of 7 metres. The manufacturer states that the sensor shall be installed in a height of approximately 2.5 m. For all rooms the installation height is between 2.30 and 3.10 m. The diagonal $\overline{AC}$ is always smaller than 5.5 m, which is below the maximal range. For all devices, test alarms are generated to ensure their functionality before starting the trial.

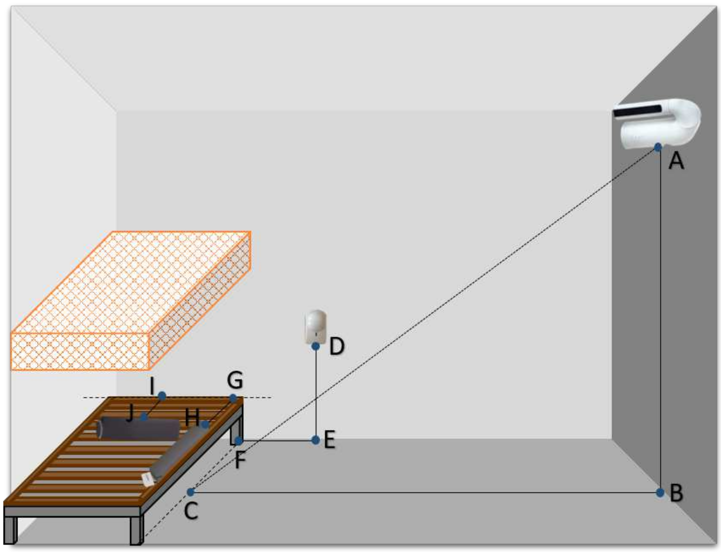

Figure 3.6: Illustration of the setting for the fall prevention evaluation, showing the distances used in Table 3.3.

3.2 Fall Detection Systems

The evaluation of fall detection devices is done in a laboratory setting comprising 10 subjects. Adapting the test scenarios from Noury et al. [16], 11 fall scenarios and 11 ADLs are set up. Having all devices installed at the same time, 660 events are carried out in total. The device's performance is compared by calculating precision and recall.

3.2.1 Products for comparison

In contrast to the devices for fall prevention, only one exemplar of each product is used for fall detection study. Via web search a list of potential devices is compiled (see Table 3.4).

Product	Company	Product	Company	Product	Company
ISA	MintT	MentorAge	Waldner Tecnologie Medicali S.r.l.	Sensoria	Sensoria Inc.
safe@home	Vitracom GmbH	Familyeye	Familyeye BVBA	Oxocare	Oxon AG
b-cared	caregency GmbH	ORME falls sensor	ORME	SMART PROTECTOR	KUTTER PROTECT GmbH
Sturzmelder	sturz-melder.de	fearless, the intelligent fall sensor	cogvis software und consulting GmbH	Fallsensor	Lifecall Hausnotruf GmbH
Angel4	Sense4Care sl	iWatch4	Apple Inc.	Grannyguard	Pikkerton GmbH

Table 3.4: Fall detection devices on the market

While three of the devices listed in Table 3.4 were still in development phase when choosing the devices (November/December 2018), one of the companies demanded the involvement of the target group when carrying out the tests which could not be fulfilled. Considering an image-based system, a smartwatch, a smartphone application and wearable device independent of a smartphone, the following products are chosen:

- *Fearless* from Cogvis and Consulting GmbH
  Already used for the fall prevention tests, the image-based sensor can as well detect falls by calculating the major orientation of a person's body on the basis of depth images [65]. A fall is detected when the main orientation of the person is parallel to the floor. Additionally, the height of the spine is considered [65].A previously defined contact person gets an alarm either via email, SMS or via radio signals.
- iWatch4
  The smartwatch from Apple (see Image 3.7) has an integrated fall detection function in their latest release which works with an accelerometer and gyroscope.

Risk rejectory and impact acceleration are used to determine when a fall occurs[12].

Figure 3.7: iWatch4 from Apple[13]

- Angel4 from Sense4Care
  The fall sensor Angel4 (see Image 3.8) works with a tri-axial accelerometer and is placed at the waist using a clamping clip or a belt. With the corresponding app, settings like emergency numbers and emergency call delay after a fall event can be set. When a fall is detected, a countdown starts that can be interrupted by the user. If the user does not stop the countdown, an emergency call is initiated. Additionally, a text message with the person's GPS location is sent to the emergency contacts.

Figure 3.8: Angel4 from Sense4Care[14]

[12] Apple Watch Series 4 - Full Announcement, https://www.youtube.com/watch?v=ScWi67nvNz8, last access on 15.08.2019

[13] Image from https://www.apple.com/at/shop/buy-watch/apple-watch, last accessed on 28.08.2019

[14] Image from https://www.sense4care.com/tienda/angel4-fall-detection/, last accessed on 28.08.2019

- Sturzmelder
  The fall detection system Sturzmelder (eng.: fall detector) is a little device worn either like a necklace, a bracelet, on a keychain or on a belt. It can be seen in Figure 3.9 and works with an accelerometer and a SIM card to contact emergency contacts in case of a detected fall. Additionally, a manual alarm can be released. When an alarm is activated, the pre-defined emergency contacts are called successively until one of them answers the phone. Additionally, a text message with the GPS location of the user is sent to all emergency contacts.

Figure 3.9: Sturzmelder[15]

- B-cared[16]
  B-cared is a mobile application using the integrated accelerometer of the phone to implement a fall detection function. Optionally, the app can be installed on chosen smartwatches like the Claptic or the Samsung Gear. If a fall is detected or the user triggers an alarm by hand, an emergency call is set automatically to the emergency contacts while also sending the GPS location via text message. Specific time points can be configured in the app where the user has to confirm that he is fine. If he does not confirm, an alarm is sent too.

3.2.2 Comparison approach

In the following evaluation, the definition of a fall by the Kellogg Group [24] is used. Due to a high risk of injury, the target group (people older than 65 years) is not participating in the performance tests for fall detection devices. Instead, they are carried out with people in a physically good condition. Dummies are not used because scenarios like falls with recovery or falls with rotation cannot be carried out with them. Despite the fact that falls are simulated and the target group is not included, methods are taken over from the literature to produce falls that are as natural as possible. First of all, Noury et al. [16] propose to avoid habituation of the movements by varying the order of the

[15] Image from `http://www.sturzmelder.de/`, last accessed on 28.08.2019
[16] Image from `https://b-cared.com/`, last accessed on 28.08.2019

sequences. Bourke et al. [104] instruct their test subjects not to break their fall. This leads to a more realistic fall since elderly people have a lower reaction time than younger ones [104].
The tests are done in a laboratory environment with participants wearing all five devices while carrying out a defined series of fall scenarios as well as ADLs. The scenarios are taken and slightly adopted from the work of Noury et al. [16], seen in Table 3.5. The lateral falls are not separated into left and right side anymore because of the minimal discrepancies between the upper peak values for acceleration in the trunk [104]. Falls from a chair and from bed are added to improve the quality of the outcome. Considering these factors, the ADLs are adapted as well. The item “cough or sneeze” is removed since its relevance is doubted. Experts gave the advise to add “binding one’s shoes” and “tossing and turning in bed” since these scenarios can cause false alarms, especially when using image-based sensors.

A search through three different papers found on Scopus with the keywords “fall”, “detection”, “evaluation”, “elderly” and “subjects” results in a steady subject number of 10 [16, 105, 106], which is also the number used in this thesis.

For each participant, the 22 scenarios are carried out 3 times. This number is based on the fact that once would be insufficient for a statistical analysis, while holding the risk of injury on a minimum level. In total, this means 66 tests per subject and 660 data points for all subjects. For evaluating the results, a sheet with all scenarios, products and trials is created in order to be filled out during the tests. If the expected outcome is reached for a scenario, the correspondent field of the relevant product is filled out with binary data (0 = expected outcome not fulfilled, 1 = fulfilled). In the end, precision and recall are calculated per product and for each subject as well as in total. Between two falls, a break of at least 10 seconds is planned considering the activation time of all sensors after an event. To receive results approaching the behaviour of a real fall, each scenario is carried out once and then the whole sequence is repeated two more times. This shall reduce the degree of familiarization with one scenario. Moreover, the subjects are asked not to break their falls. Additionally, protectors are provided to decrease the fear of injury and thus, to increase the naturalness of the movements.

3.2.3 Setting

While the fearless sensor is mounted on a tripod (see Figure 3.10) in a height of 1.70 metres, the other devices have to be worn by the subjects. Before starting the tests, alarms are provoked for each device to ensure their functionality. Problems arose with the Angel4 since the application could not have been found on the Google Playstore. After contacting the company, an APK file was provided on their website. The download and installation worked out, but still problems with the app occurred since no alarm could be provoked with the default settings suggested in the manual. Being in contact with the company trying to find a solution, the problem could not have been solved until the start date of the tests. Thus, the device is excluded from the tests.
The iWatch is worn on the wrist (setting: left hand), the phone equipped with the mobile

#	Category	Description	Expected Outcome
1	Backward fall	Ending sitting	Positive
2		Ending lying	Positive
3		Ending in lateral position	Positive
4		With recovery	Negative
5	Forward fall	On the knees	Positive
6		With forward arm protection	Positive
7		Ending lying flat	Positive
8		With rotation, ending in lateral position	Positive
9		With recovery	Negative
10	Lateral fall	Ending lying flat	Positive
11		With recovery	Negative
12	Chair	Fall from chair forwards	Positive
13		Slipping from chair	Positive
14	Bed	Falling from bed	Positive
15	Syncope	Vertical slipping against a wall finishing in sitting position	Negative
16	Sitting	Fall down on a chair, sit, then stand up	Negative
17		Sit down on floor, then stand up	Negative
18	Bed	Lying down and stand up	Negative
19		Toss and turn in bed (2-3 times)	Negative
20	Walking	A few metres	Negative
21	Picking up	Catching something on the floor, then rise up	Negative
22	Binding one's shoes	While sitting on bed	Negative

Table 3.5: Fall detection evaluation scenarios, adapted from [16]

application b-cared is fixed on the arm and the device sturzmelder is worn like a necklace. Figure 3.11 shows the systems worn on the body.

Figure 3.10: Installation of the image-based device fearless on a tripod.

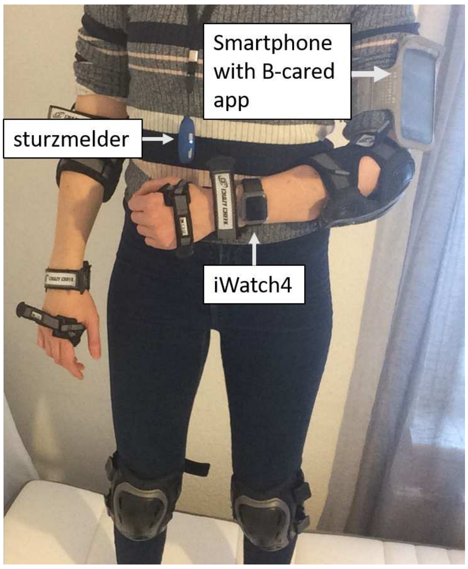

Figure 3.11: Wearable devices worn on a subject with knee, hand and elbow protectors.

For the sturzmelder, different mounting locations are possible (necklace, bracelet, belt). Since the company does not recommend a certain position and the tests must be carried out with one device only, it is worn as a necklace throughout all of the tests. The fearless sensor offers the possibility to send alarms either via SMS, e-mail or radio receiver. In the test setting, solely alerting via SMS is used.
The fearless sensor is mounted on the tripod in the same position and height for all subjects. The falls are carried out on a thin mattress to reduce the risk of injury. The mattress has a fixed position, marked on the floor for reasons of reproducibility. The setting can be seen in Figure 3.12.

For the ADLs, a sofa is used as a bed, with the dimensions 42x200x80cm (height x length x width, see Figure 3.12). The chair in use has a height of 50 cm.

3.3 User Acceptance Approach

For analysing the user acceptance of AAL devices, the adapted UTAUT2 model by Halbach et al. [20] is used. The qualitative prestudy is taken from the research team as a basis for the questionnaire. As suggested in their work, an AAL scenario is presented to the participants to make them familiar with the topic. One part consists of gaining information about the ATT and experience with AAL devices and with caring for another person. Then, the acceptance of AAL and specifically of fall sensors is evaluated via

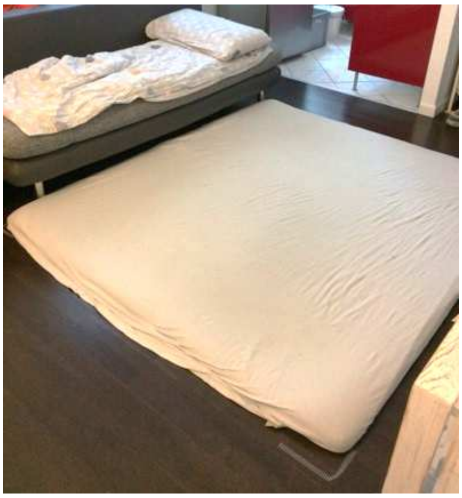

Figure 3.12: Setting for lab fall tests.

UTAUT dimensions. The dimension PV is removed because no specific product, but only example scenarios are used. Finally, the dimensions PE, EE, SI, FC, HM, EH, BI, PC and DI are implemented. Figure 3.13 pictures the dimensions and terms used in the context of the applied user acceptance model.

For each dimension, two questions are created in order to ensure that the dimensions are well understood on the one hand, and to minimize the time needed to complete the questionnaire on the other hand. The last section is for gaining demographic information such as age and education level. The questionnaire is created with LamaPoll[17]. The translated questionnaire (original in German) can be seen in the Appendix and is exemplary for the user group of people aged 65 and older. The design of the attached questionnaire is more compact than the web version and leaves out spaces for comments. Apart from conditional questions all of the questions are set mandatory for receiving only complete questionnaires. A 6-Point-Likert scale is used for the UTAUT items as well as for the ATT section to make the participants decide for one side while still leaving options within one side.

Target group

The following groups are considered as target group due to their increased contact with AAL products: nursing staff, healthcare management, technical staff in healthcare facilities, end-users (persons older than 65 years) and relatives. Having multiple target groups, five different questionnaires are created, varying only little from each other while considering the groups' perspective.

Distribution

Social media and messenger apps are used to distribute the questionnaire link. To gain

[17] https://www.lamapoll.de/, last accessed on 28.08.2019

ATT	Attitude Towards Technology	the general attitude of a person towards technology
UTAUT	Unified Theory of Acceptance and Use of Technology	a model to describe the factors influencing user acceptance of technology
AAL	Active Assisted Living	a concept aiming to enable individuals to live an active, socially involved and independent life up to old age
PV	Price Value	the consumers' cognitive tradeoff between perceived benefits and the monetary cost for using the product
PE	Performance Expectancy	describes how an individual believes that using a system will increase his job performance
EE	Effort Expectancy	the degree of ease associated with the use of the system
SI	Social Influence	the degree to which an individual perceives that important other believe he should use the new system
FC	Facilitating Conditions	the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system
HM	Hedonic Motivation	fun or pleasure derived from using a technology
EH	Experience and Habit	Experience: the opportunity to use a technology for a certain time Habit: the extent to which people tend to perform behaviours automatically because of learning
BI	Behavioural Intention	a person's intention to use the system
PC	Privacy Concerns	a person's fear in terms of privacy and data security
DI	Design and Integration	the perception of the system in visual aspects

Figure 3.13: Dimensions and terms in the context of user acceptance.

a more representative sample, people are asked to spread the link further within their environment. Apart from the digital link, a printed version is created to reach older people as well. The printed version is handed out within the neighbourhood. Moreover, people in the Oberlaa Kurpark of Vienna are asked to participate in the survey.

Evaluation methods

As a first step of the evaluation of the questionnaire, all incomplete surveys are eliminated.

With the remaining questionnaires, the general and demographic questions are analysed by comparing them with available statistics. For each question with a 6-Point-Likert score, the percentages of participants marking 'slightly (dis-) agreeing', '(dis-) agreeing' and 'strongly (dis-) agreeing' are added up. If there are two questions per category, the mean is calculated. Particularly outstanding questions, which the majority of participants marked with 'strongly agree' or 'strongly disagree' are highlighted. Finally, the differences and similarities between the groups are pointed out.

CHAPTER 4

Results and Discussion

For evaluating the devices for fall prevention, depth image sequences are recorded during the 28-days field experiment. From these image sequences, all actual getup events are extracted, documenting their time stamps. These time stamps are compared with the data from the Raspberries containing the time stamps of alarms sent by the test devices. Using that data, the alarm behaviour of the devices can be compared using precision and recall. For the fall detection devices, the binary data received from the laboratory tests can be directly used to calculate these rates. Apart from the performance, the time delay, battery life, installation and maintenance effort, price and size are compared using consistent units.

4.1 Fall Prevention Evaluation

After the test-phase of 28 days, the devices are dismounted and the data from the hard disks are evaluated, containing 239 getup events. The majority of events is gathered from one subject only. The number of getup events per participant can be seen in Table 4.1.

	Participant 1	Participant 2	Participant 3	Participant 4
Getups	0	205	15	19

Table 4.1: Total number of getup events per participant recorded during testing period

In the room of Participant 2, the position of the Optex sensor could not be mounted within the suggested distances, which might have distorted the results. The motion-based recording on one hard disk was incomplete and thus, fewer sequences could be analysed. Two of the participants regularly unplugged the test device, which additionally reduced the number of data.

4.1.1 Performance

The performance of the different devices is compared by the calculation of precision and recall. Figure 4.1 shows the mean precision and recall of all devices used in the test setting. The precision gives information about the usefulness of the results, meaning the relation between the correctly detected events and the sum of correctly detected events plus the number of false alarms.

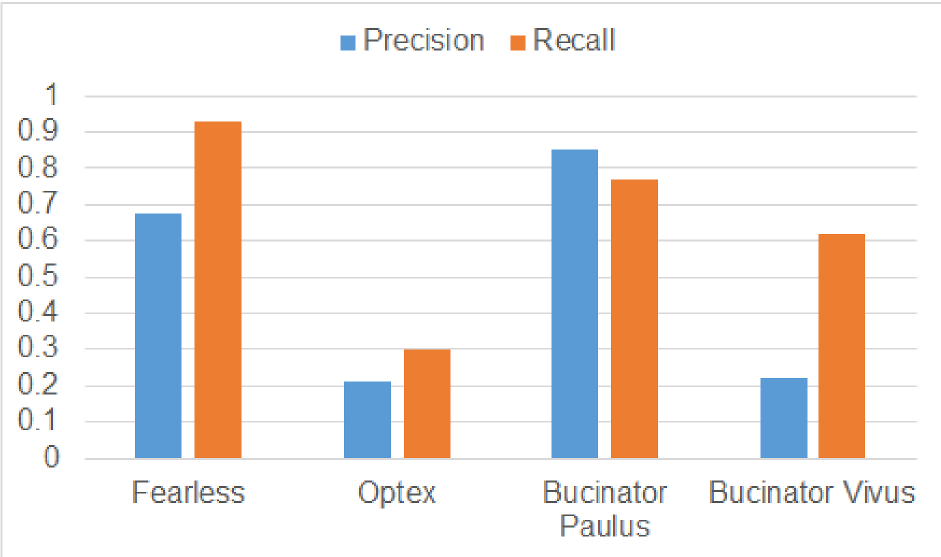

Figure 4.1: Mean precision and recall for the different devices for fall prevention.

The fall sensor fearless has an average precision of 0.68 over the total testing period. The Bucinator Paulus has a mean precision rate of 0.85. A precision of 1 is held for 5 days, but after the 12^{th} day, no more data is delivered (see Figure 4.2). One Bucinator Paulus delivers data for three days only. The reason for that is that the participant unplugged the installed system and wished to not use it any further. For the other Bucinator Paulus, data is recorded for a total of 8 days, with 4 days of gaps, where no data was sent. After the 12^{th} day, no more data is delivered. While the precision of the Optex sensor is 1 for the first 3 days, it drops and stays low for the rest of the period with a total mean value of 0.21. The precision value for the Bucinator Vivus varies between 0.02 and 0.67 (mean precision 0.22).
Subtracting the precision from 1 reveals the FP rate, which describes the percentage of FP events within all detected events. The number of false alarms per day per device is shown in Figure 4.2. The highest number of false alarms is caused by the Bucinator Vivus, namely on average 27.00 per day, summarizing the number of all four subjects. After having talked to the company owner of Bucinator, the problem could have been an incorrect calibration process, which is more sensitive for Bucinator Vivus than for Bucinator Paulus. The mean value of false alarms is 19.12 per day for the Optex sensor, 3.96 for fearless and 0.44 for Bucinator Paulus. Due to limited options of mounting the

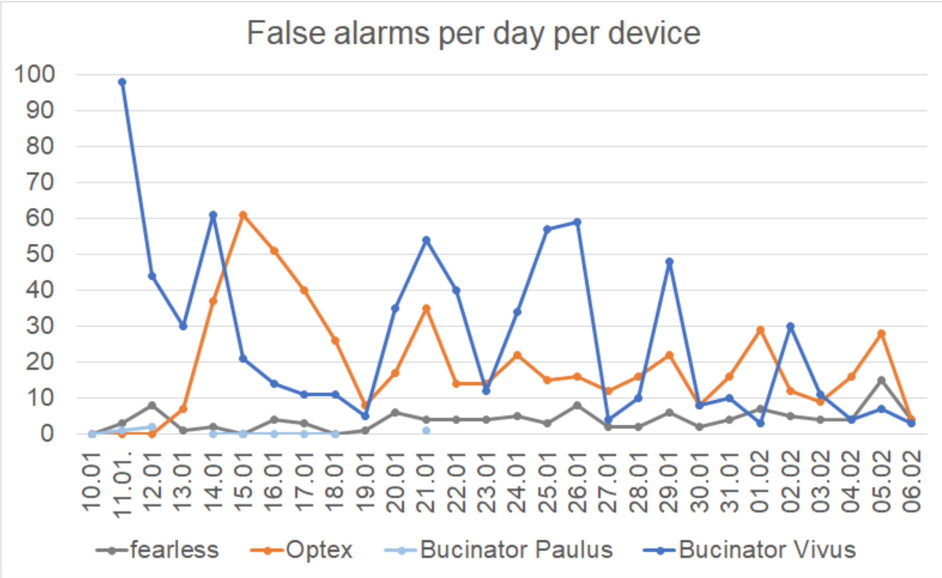

Figure 4.2: Number of false alarms per day per device occurred during the fall prevention tests.

Optex sensor in the rooms, some of them had to be installed besides a bedside table or next to a chair that should not be moved, which might have led to inferior results.
The recall or also called sensitivity, describes the completeness of the results, meaning the percentage of discovered events among all actually occurred getup events. Fearless has discovered the most getup events with a mean sensitivity of 0.93. The Bucinator Paulus holds a value of 0.77, while it is 0.62 for the Bucinator Paulus and 0.30 for the Optex sensor. Subtracting the recall from 1 delivers the rate of missed alarms. The number of missed alarms per day per device is shown in Figure 4.3. The Optex sensor misses the most alarms with an average of 6 alarms per day. The device Bucinator Vivus holds a mean value of 3 for missed alarms, while it is 1.44 for the Bucinator Paulus and 0.71 for fearless.

4.1.2 Time delay

Fall prevention devices are built to assist people with a higher risk of falling when getting up from bed. Thus, the moment of the alarm is essential. Since the exact time of the event and the time of the alarm is known, the time delay can be calculated. Figure 4.4 shows a boxplot of the time delays of all the devices used in the study. A negative value means that the alarm is received before the event occurs. The fall sensor fearless has the smallest and the Optex sensor the biggest variation in the time delay, without considering the outliers. Fearless alarms in a small time range around the event, while the Bucinator products (Paulus and Vivus) send an alarm on average 39.88 seconds before the person gets up from bed. The Optex sensor alarms between 62.00 seconds before and 34.00

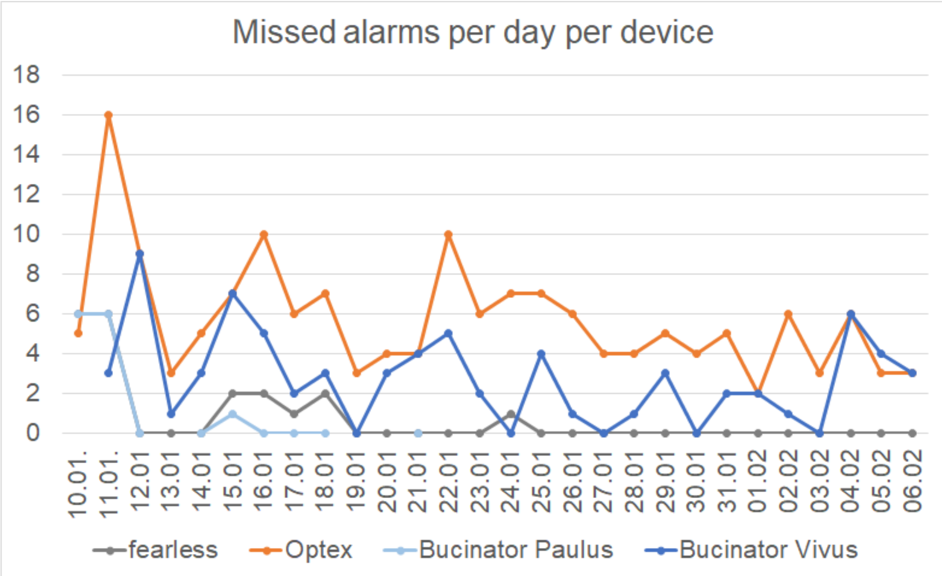

Figure 4.3: Number of missed alarms per day per device occurred during the fall prevention tests.

seconds after the event, with a mean time delay of -6.23 seconds, meaning 6.23 seconds before the event. The mean time delay of all devices can be seen among other factors like costs, battery life or installation effort, in Table 4.2.

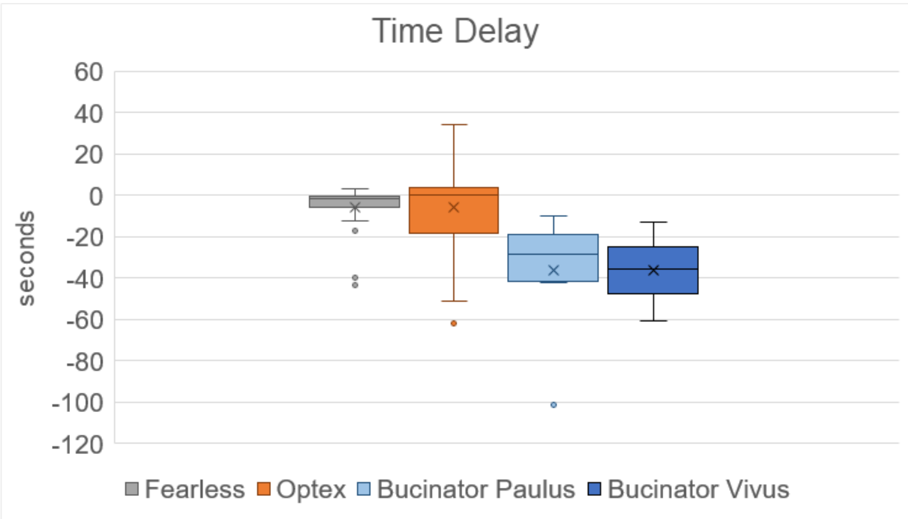

Figure 4.4: Time delay between the event and the alarm in seconds for fall prevention devices.

Category	Fearless	Optex	Bucinator Paulus	Bucinator Vivus
Mean time delay in seconds	-6.05	-4.18	-35.98	-36.07
Privacy	depth images, getup monitoring	getup monitoring	getup monitoring	getup monitoring
Battery life	infinity	1 year	1 year	1 year
Installation effort in minutes	20	5	< 5	< 5
Maintenance effort	none	changing battery	changing battery	changing battery
Price	850.00€	345.00 €	486.90 €	1040.00 CHF
Size ($l \times w \times d$) in cm	approx. $27 \times 10 \times 10$	approx. $10 \times 13 \times 6$	approx. $60 \times 10 \times 2$	approx. $50 \times 15 \times 2$

Table 4.2: Comparison of additional factors for the tested fall prevention devices

4.1.3 Privacy protection

The fearless sensor works with depth images, which means that faces are not visible (see Figure 4.5). Only the overall shape of a person can be seen. In case of an event, the depth image is sent to a web platform and can be seen by the customer and by selected company staff. No access to continuous depth image recording is given since the processing takes place within the sensor, before sending the image via internet.

The Optex sensor detects movement within a certain angle range by using infrared. No images or videos are created. Both products from Bucinator are placed under the mattress and work with the applied force on the sensor. All of the four tested devices can be used to gain information about when a person leaves or enters a room, or when a person gets out of bed. Although this can be regarded as privacy intruding or as a limitation of freedom, a continuous surveillance is not possible. Table 4.2 summarizes the features used by the devices that can be regarded as affecting a person's privacy.

4.1.4 Battery life

The fall sensor fearless is supplied with electricity via cable. Thus, it does not have to be recharged or equipped with new batteries. Otherwise, a plug socket is required for using the sensor. The Optex sensor is provided with a battery. The manufacturer states that the battery life in standby is about three years and recommends a battery exchange every year. The Bucinator Paulus works with a CR2032 battery and lasts for about a

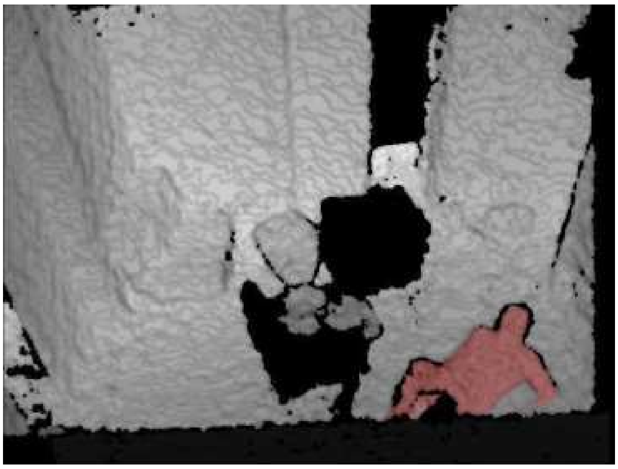

Figure 4.5: Exemplary depth image from fearless.

year, depending on the usage. If the red LED still blinks three seconds after receiving an alarm, the battery has to be exchanged. The Bucinator Vivus works with AA batteries which also last about one year. In contrast to the Bucinator Paulus, an integrated control unit sends an alarm which can not be quit when the battery level has reached a certain threshold. An overview of the battery life of the different devices can be seen in Table 4.2.

4.1.5 Installation effort

The installation of fearless comprises the following points: mounting the device on the wall or on the ceiling, either with adhesive tape or with screws, connecting the device with the internet following the instruction manual, and (optional) linking the device to an existing call system. If the alarms are chosen to be sent via text message or via email, or if settings like time-dependent functionality (e.g. alarms only at night) are required, a configuration on the web platform is required. The overall installation took about 20 minutes (see Table 4.2).
To install the Optex sensor, the device has to be opened in order to switch from test mode to real mode. To change the mode from wide-angle to long-distance or vice versa, the sensor has to be taken out and inserted again in the upside down position. The sensor is mounted on the wall or another object via adhesive tape. Mounting the device took about 5 minutes.
The device Bucinator Paulus has to be put under the mattress with the correct orientation. This also applies for the Bucinator Vivus, which has an additional control unit that can be fixed via a hook. Both products from Bucinator as well as the Optex sensor have to be connected to a receiver. For the fearless sensor, the customer can chose between getting the alert via receiver, SMS or mail. Both Bucinator products were installed in less than 5 minutes.

4.1.6 Maintenance effort

Concerning the fearless sensor, once it is installed, the user does not have to interact with the device anymore. The user, his or her caregiver has the opportunity to take a look at the events of the sensor on the web platform, add users or change settings. If the sensor is moved from one room to another, the user has to think about the right position for the device or ask the support for advice.
The only maintenance tasks for the Optex and Bucinator Paulus sensors is changing the battery once a year. If the performance of the Bucinator Vivus is not as desired, it might help to recalibrate the device. This can be done by removing the device from the mattress, disconnecting the sensor from the control unit, and repeating the installation tasks.

4.1.7 Price

The Bucinator Vivus is the most expensive device with 1040.00 CHF[18]. Fearless is currently only available for B2B customers for a price of 850 €[19]. The Optex sensor is the cheapest product with 345.00 €[20], followed by the Bucinator Paulus with 486.90 € [21].

4.2 Fall Detection Evaluation

For the evaluation of different devices used for fall detection, 10 participants attend the practical tests. People from the writer's personal circle are asked to participate while considering a balanced gender ratio. The attendees are equipped with all the products while receiving information about the study and the devices. Before carrying out the fall, the ideal movement is explained.
Table 4.3 describes the statistical information about the attendees, containing age, gender, weight and height. The distribution of the gender is equally with 50% female and 50% male. All participants are between 21 and 28 years old and physically fit, fulfilling the predefined criteria.

4.2.1 Performance

In contrast to the tests for fall prevention, the TN rate is now known. Nevertheless, precision and recall are used. That is because knowing about the false-alarm rate instead of how many non-falls correctly do not cause an alarm is considered to have a higher informative value. Figure 4.6 demonstrates the mean precision and recall of the tested

[18] 941.57 €, exchange rate calculated on 26.07.2019, https://www.kuhnbieri.ch/de/alarmsystem-bucinator-mit-eldat-funksender-4.html, last accessed on 28.08.2019
[19] B2B price, information from the corporal management, 24.07.2019
[20] https://winkertec.de/produkt/infrarot-bewegungsmelder/, last accessed on 28.08.2019
[21] https://www.hospital-textil.at/produkte/patientenalarmsystem/, last accessed on 28.08.2019

Participant #	Age	Gender	Weight [kg]	Height [m]
1	21	m	84	1.78
2	25	w	55	1.66
3	24	w	52	1.59
4	26	w	55	1.72
5	25	m	65	1.82
6	27	m	80	1.80
7	28	m	91	1.95
8	28	m	70	1.75
9	24	w	53	1.58
10	26	w	59	1.70

Table 4.3: Statistics of participants in fall detection study

devices summed up for all participants, while Figures 4.7- 4.8 demonstrate the precision and recall of the tested devices for each participant. A missing bar in the precision graph means that in the test sequences of the participant, the device did not produce any alarm.

The device fearless has the most steady precision rate with a mean value of 0.92 (mean false alarm rate of 0.06) summed up for all participants. In total, 0.65 falls are detected by fearless. The iWatch4 has a precision of 1 for Participants 5 - 7, but has no bar for the other participants (see Figure 4.7). This means that the false alarm rate for the occurred alarms is 0, but 98.2 % of falls are missed (mean recall rate is 0.018, see Figure 4.6). The device sturzmelder has a precision of 0.78, with a low false alarm rate between 0 and 0.03. Only 6 % of falls are detected by sturzmelder. The mobile application b-cared has a mean precision rate of 0.5, and a mean recall of 0.006. Figure 4.8 shows that for Participants 1-8, no alarm is detected by b-cared. The mean recall value derives only from Participant 9 and 10.

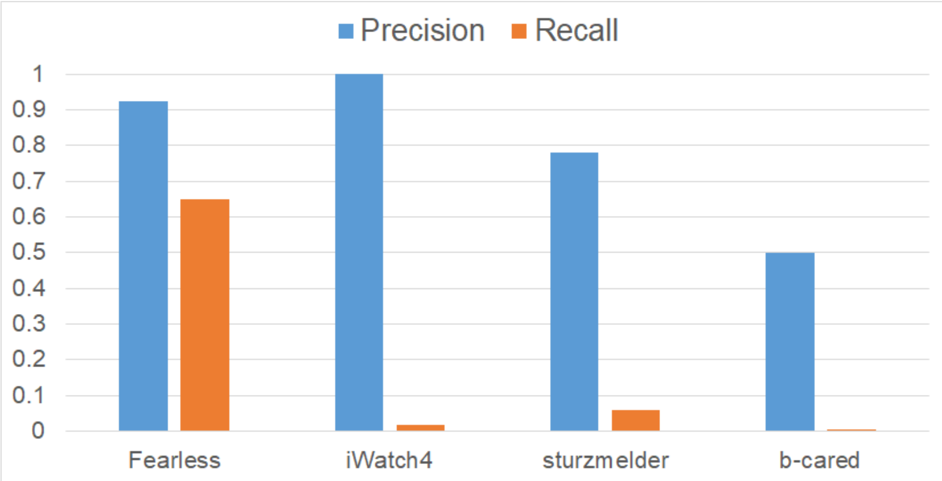

Figure 4.6: Mean precision and recall for the different fall detection devices.

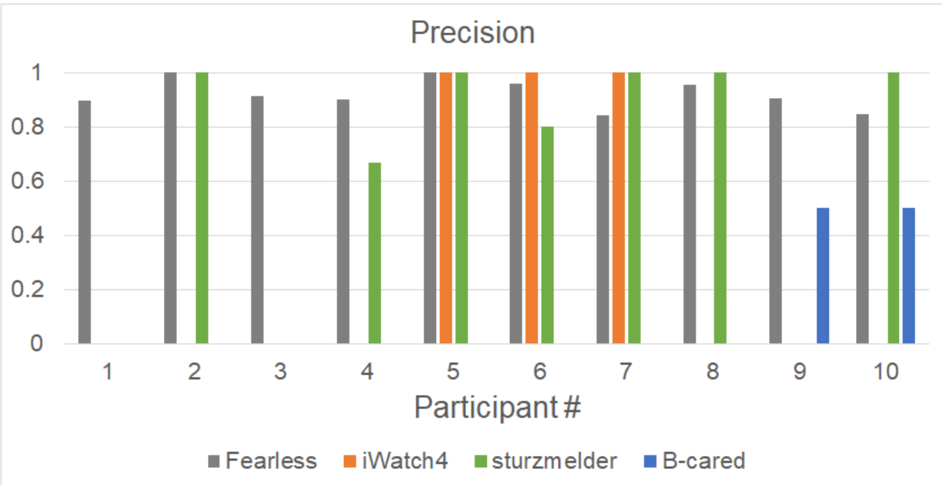

Figure 4.7: Mean precision for the different fall detection devices per participant.

The expected outcomes of the chosen fall and ADL scenarios as well as the average percentage a device has reached are shown in Table 4.4. For example, in 53% of all falls in the category "backward fall, ending sitting" (summed up for all subjects), the expected outcome is reached by the fall sensor fearless. Figure 4.9 illustrates the TP rate for each fall scenario and device. The TN rate for each ADL and device is not shown.
The expected outcomes are based on the definition of a fall after the Kelloggs Institute [24]. Since different definitions of a fall are used, the outcomes of different devices can vary. For example, the image-based sensor fearless detects a person lying or sitting on the floor as a person in need and therefore also alerts in the categories "syncope" (33.33%)

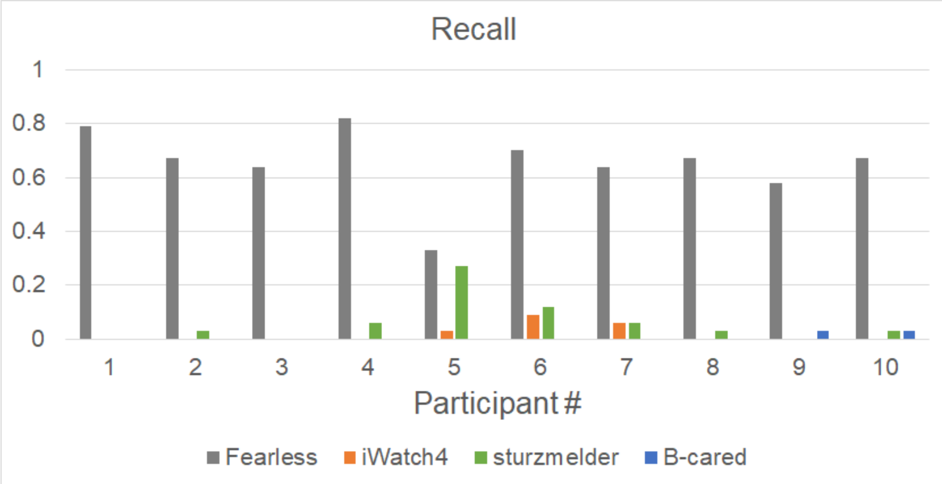

Figure 4.8: Mean recall for the different fall detection devices per participant.

and "sitting on the floor" (16.66%, see Table 4.4, Row 15 and 17).

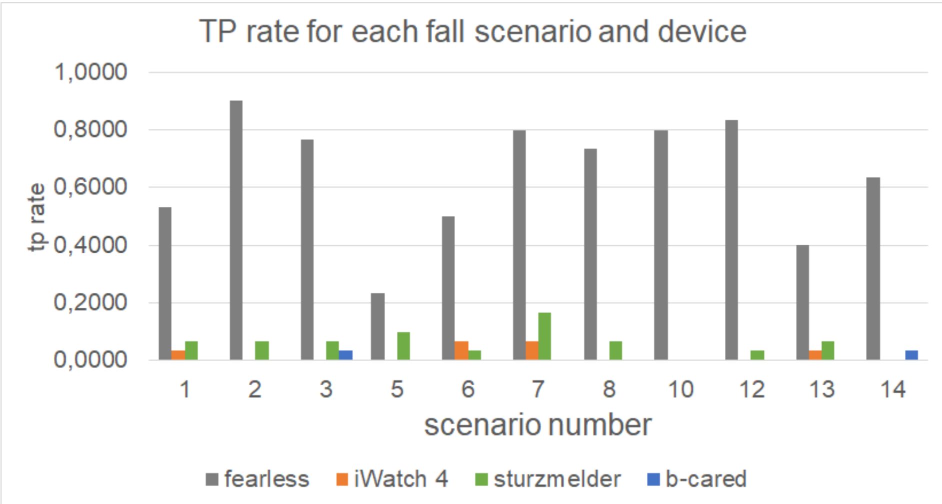

Figure 4.9: TP rate per fall scenario and device.

The highest detection rate by fearless is when falls ending with lying flat on the ground occur (backward 90%, forward and lateral 80% and falls from the chair with 83.33%). The iWatch4 detects 3.33% of backward falls ending sitting and slipping from a chair as well as 6.67% of forward falls with arm protection and forward falls ending lying flat. All other falls are not detected while also no false alarms occur. The device sturzmelder detects 16.67% of forward falls ending lying flat, while all other falls are detected with an average rate of 6.67% and below. When falling on a chair while sitting down or simulating

#	**Category**	**Description**	**Expected Outcome**	fearless	iWatch4	sturz-melder	b-cared
1	Backward fall	Ending sitting	Positive	53 %	3 %	7 %	0 %
2		Ending lying	Positive	90 %	0 %	7 %	0 %
3		Ending in lateral position	Positive	77 %	0 %	7 %	3 %
4		With recovery	Negative	100 %	100 %	100 %	100 %
5	Forward fall	On the knees	Positive	23 %	0 %	10 %	0 %
6		With forward arm protection	Positive	50 %	7 %	3 %	0 %
7		Ending lying flat	Positive	80 %	7 %	17 %	0 %
8		With rotation, ending in lateral position	Positive	73 %	0 %	7 %	0 %
9		With recovery	Negative	100 %	100 %	100 %	100 %
10	Lateral fall	Ending lying flat	Positive	80 %	0 %	0 %	0 %
11		With recovery	Negative	100 %	100 %	100 %	97 %
12	Chair	Fall from chair forwards	Positive	83 %	0 %	3 %	0 %
13		Slipping from chair	Positive	40 %	3 %	7 %	0 %
14	Bed	Falling from bed	Positive	63 %	0 %	0 %	3 %
15	Syncope	Vertical slipping against a wall finishing in sitting position	Negative	67 %	100 %	97 %	100 %
16	Sitting	Fall down on a chair, sit, then stand up	Negative	93 %	100 %	97 %	100 %
17		Sit down on floor, then stand up	Negative	73 %	100 %	100 %	97 %
18	Bed	Lying down and stand up	Negative	100 %	100 %	100 %	100 %
19		Toss and turn in bed (2-3 times)	Negative	100 %	100 %	100 %	100 %
20	Walking	A few metres	Negative	100 %	100 %	100 %	100 %
21	Picking up	Catching something on the floor, then rise up	Negative	100 %	100 %	100 %	100 %
22	Binding one's shoes	While sitting on bed	Negative	100 %	100 %	100 %	100 %

Table 4.4: Fall detection evaluation scenarios with the outcome of the different devices given in percentage, rounded.

a syncope, alarms occur in 3.33% of all repeats. The mobile application b-cared detects 3.33% of backward falls ending in lateral position and falls from bed and does not detect any further falls. A lateral fall with recovery and sitting down on the floor is detected as a fall once for each scenario within the total number of tests.

Different than written in the user's manual, 12 out of 17 times the device sturzmelder sent solely a text message instead of calling the emergency numbers and sending the message with the GPS data. If this was the case during the test, the event was still marked with 'alarmed' in the evaluation sheet because the relative or the care worker is still informed about the incident. Nevertheless, users might not accept the product and develop mistrust.
During the installation process of the fearless sensor it has been found out that dark floors prevent the correct detection of falls. Figure 4.10 shows the depth image on the fearless platform without having placed the grey mattress, and Figure 4.11 demonstrates the setting with the mattress. The blue marked area shows which part of the image is detected as the floor. Behind the mattress, one can still see the black area where the floor is not detected as such. The color of the floor can be seen in Figure 3.12.
Using mostly accelerometer-based devices, knowing the impact speed and the thresholds used by the devices would improve the ability to make statements about the products' performances. In this study, the impact speed is not raised. For further studies, it is suggested to carry out the tests with two user groups, doing the fall scenarios with young and fit people like done in this thesis, and performing the ADLs with people from the target group.

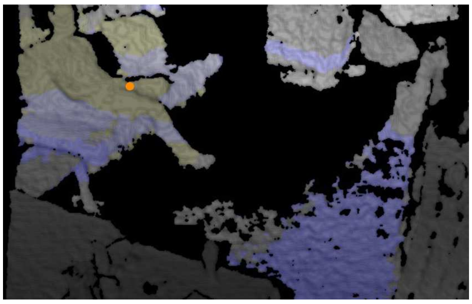

Figure 4.10: Depth image of the test setting with the incorrectly detected floor.

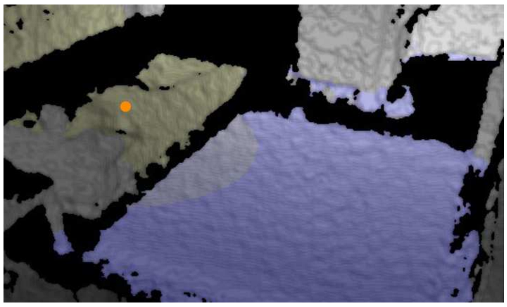

Figure 4.11: Depth image of the test setting with the correctly detected floor.

4.2.2 Time delay

The time delays occurring between an event and the alarm are summed up for every device and shown in Figure 4.12. Fearless has the largest range of time delay lying between 7 and 25 seconds. The time delay for b-cared varies between 8 and 10 seconds, while it is 2-4 seconds for the iWatch4 and 2-6 seconds for the device sturzmelder. Timely help is of high importance for people who cannot get up on their own again. All of the tested devices send an alarm in under 30 seconds after the fall event, which enables early help. Table 4.5 shows the mean time delay of each device as well as the other investigated factors privacy, battery life, installation and maintenance effort, price and size.

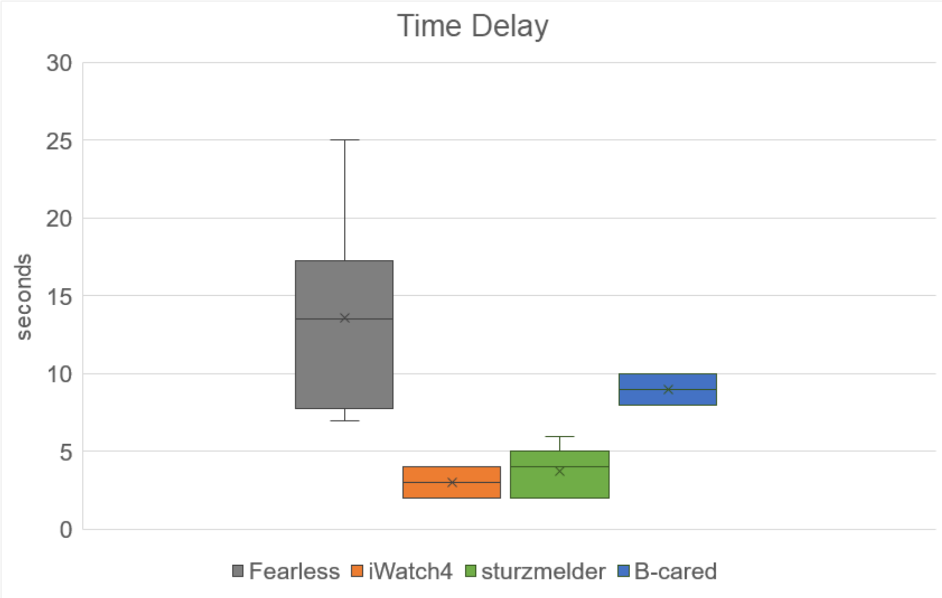

Figure 4.12: Time delay between the event and the alarm in seconds for the evaluated fall detection systems.

4.2.3 Privacy protection

It has already been explained how fearless deals with privacy. In case the user does not move within one minute after a fall, the iWatch4 sends a text message containing the GPS data of the user to the previously stored emergency contacts. Additionally, the emergency contacts are called, which allows them to listen in automatically. On the other side, there is the option to cancel the alarm if the user is still capable of doing so. The device sturzmelder also alarms the emergency contacts when the user cannot move or press the emergency button. Text messages with the time of the fall, falling speed, battery level of the user's phone and GPS data are transmitted. The mobile application B-cared works in the same way, sending positioning data in case of a fall and inactivity of the user to selected phone numbers.

4.2.4 Battery life

Apart from the device fearless, which gets its power from an electric cable, all other devices have to be charged in different time intervals (see Table 4.5). Depending on the usage, the iWatch4 has to be charged via USB cable every one to three days. The fall sensor sturzmelder can also be charged via USB every two or three days. Since b-cared is a mobile application, the functionality depends on the power supply of the smartphone.

Category	Fearless	iWatch4	sturzmelder	B-cared
Mean time delay in seconds	13.60	3.00	3.71	9.00
Privacy	depth images	GPS	GPS	GPS
Battery life	power supply by cable	1-3 days	2-3 days	dependent on the smartphone
Installation effort in minutes	15	15	5	5
Maintenance effort	none	recharging	recharging	none
Price	850.00 €	429.00 €	195.00 €	14.90€ /month
Size ($l \times w \times d$) in cm	approx. $27 \times 10 \times 10$	$12 - 20 \times 3.4 \times 1.07$	approx. $5 \times 7 \times 2$	depends on phone

Table 4.5: Comparison of additional factors for the tested fall detection devices

4.2.5 Installation effort

The installation procedure for the fearless sensor is equal to that already described when using it for fall detection. The duration is about 15 minutes. On the web platform, one can chose to get the alarms for either a fall event, a getup event, none or both. For the fall detection tests, only alarms for falls are sent.
When unpacking the iWatch4 the first time, configuration settings have to be done, as well as linking the watch to an iPhone. The activation of the fall detector can be carried out in the settings. The overall setup takes about 15 minutes.
For the fall sensor sturzmelder, the setup works via SIM card. Therefore, a SIM card is inserted into the device. The configuration settings are done by sending one or more text messages from a smartphone to the phone number of the device. In total, the installation takes about five minutes.
B-cared is a mobile application, which can be connected to specific smartwatches, but can also be used without one. For the fall detection tests, only the app by itself is used. The configuration includes setting up emergency phone numbers and personal data and takes about five minutes.

4.2.6 Maintenance effort

The iWatch4 and the device sturzmelder have to be recharged about every 1-3 days. For the mobile application b-cared, the maintenance effort in Table 4.5 is given as “none” because not the app, but the phone has to be recharged. Thus, the app itself does not cause additional maintenance apart from changing emergency numbers or settings, which can be applied for all devices.

4.2.7 Price

At a price of 850.00€[22], the fearless sensor is the most expensive among the devises tested. The iWatch4 is the first iWatch with the integrated fall detection algorithm. Thus, older versions cannot be used and the new version for 429.00 €[23] has to be purchased. The device sturzmelder has a lower price with 195.00 € [24].
B-cared is not a device, but a mobile application and therefore is the cheapest product among the ones evaluated (14.90€ /month[25]). In the tests, the application is not used together with a smartwatch, which could deliver different results while driving costs further. Table 4.5 reflects an overview of prices.

4.3 User Acceptance Evaluation

A survey is conducted in order to assess the acceptance of fall sensors and AAL technology in general. Furthermore, the acceptance from different groups - technical staff, nursing staff, healthcare management, end users (people aged 65 and older) and relatives - is risen. The survey is done with the online tool LamaPoll[26]. Considering only complete questionnaires, 367 participants are reduced to 189, from which 67% are women and 29% are men (the other 4% did not specify their sex). The questionnaire could be accessed online over a continuous period of two months.

4.3.1 Demographic information

Age and gender
Table 4.6 shows the gender distribution of the participants. Since the questionnaire was mostly completed by Austrians (89.95% from Austria, 6.88% from Germany, 1.59% from UK, 0.53% from Canada), the results are compared with known statistics from the Austrian population. 43.32% of people aged 65 and older living in Austria in 2019 are male[27], while it is 36% for the participants of the questionnaire.
In the age group of 15-64, the amount of men in Austria in 2019 (49.18%) is nearly equal to that of women[27]. In the questionnaire, 42% of relatives (aged between 15 and 64) are

[22] B2B price, information from the corporal management, 24.07.2019
[23] `https://www.apple.com/at/shop/buy-watch/apple-watch`, last accessed on 28.08.2019
[24] `http://www.sturzmelder.de/sos-notruf-mit-falldetektor.html`, last accessed on 28.08.2019
[25] `https://b-cared.com/costs`, last accessed on 28.08.2019
[26] `https://www.lamapoll.de/`, last accessed on 28.08.2019
[27] Population Structure 2019, Statistik Austria, `http://www.statistik.at/web_de/statistiken/menschen_und_gesellschaft/bevoelkerung/bevoelkerungsstruktur/bevoelkerung_nach_alter_geschlecht/index.html`, last accessed on 28.08.2019

men, while 8% did not specify their gender. 81% of nursing staff in stationary care and 91% in mobile care are female[28], which is similar to the 80% reached in the survey.

A German statistics institute investigated the staff structure in healthcare facilities with the result that 68.03% of accountant, logistic and administration staff in hospitals is female, whereas it is 81.70% in care homes[29]. Due to similarities between the Austrian and the German standards, healthcare structures and population distribution, the gender distribution in healthcare management is assumed to be nearly equal in Austria.

group	**n**	**male**	**female**	**no answer**
users (65+)	25	36%	60%	4%
nursing staff	91	19%	80%	1%
relatives	36	42%	50%	8%
healthcare management	33	39%	58%	3%

Table 4.6: Gender groups of the survey participants

Table 4.7 shows the age distribution of participants. Within the age range 15-64, 16.42% of Austrians are aged 15-24, 20.42% are between 25 and 34 years old, 19.75% between 35 and 44, 22.69% between 45 and 54 and 20.72% are aged 55-64 (satus quo 2019)[30]. The main part of participants within the group of relatives (55.55%) is aged 25-34, while there are no participants in the age group ranging from 55 to 64. The percentages of the groups aged 15-24,35-44 and 45-54 are similar to the results in the questionnaire (cf. Table 4.7).

People aged 65 and older participating in the questionnaire are on average 76 years old with an age range between 65 and 90. 24% are between 65 and 69 years old, 20% between 70 and 74, 20% between 75 and 79, 16% between 80 and 84, 12% between 85 and 89 and 18% are between 90 and 94. Despite some deviations, especially in the oldest range, this distribution has similarities to the age structure of the Austrian population above 65 (65-69 years: 26.65%, 70-74 years: 23.22%, 75-79 years: 22.90%, 8-84 years: 13.78%, 85-89 years: 8.56%, 90-94 years: 3.90%)[30].

Comparing the age distribution of the healthcare staff (nursing staff and healthcare management) from the questionnaire with the numbers in Germany in 2016, one can see

28 Pflege und Betreuung älterer Menschen in Österreich, Arbeiterkammer Österreich, 2014 https://media.arbeiterkammer.at/PDF/Pflege_und_Betreuung_2014.pdf, last accessed on 28.08.2019

29 Personal in Krankenhäusern und Vorsorge- oder Rehabilitationseinrichtungen am 31.12.2017 nach Berufsgruppen, Landesbetrieb Information und Technik Nordrhein-Westfalen, https://www.it.nrw/statistik/eckdaten/personal-krankenhaeusern-und-vorsorge-oder-rehabilitationseinrichtungen-am, last accessed on 28.08.2019

30 Population pyramide 2019, Statistik Austria, http://www.statistik.at/web_de/downloads/webkarto/bev_prognose_neu/#!y=2019&a=55,65&g, last accessed on 28.08.2019

that the distribution in the target group is more spread, especially in the groups with people aged 15-24 and 55-64[31].

group	n	mean age	age 15-24	age 25-34	age 35-44	age 45-54	age 55-64
users (65+)	25	76	-	-	-	-	-
nursing staff	91	39	4.40%	31.87%	31.87%	26.37%	5.49%
relatives	36	34	11.11%	55.55%	16.67%	19.44%	0.00%
healthcare management	33	43	0.00%	24.24%	33.33%	33.33%	12.12%

Table 4.7: Age groups of the survey participants

Education level

In the group of people aged 65 and older, 40% finished an apprenticeship, while 36% attended a vocational school. 12% have a university degree, 8% have a diploma and 4% graduated high school. Participants of the relatives group have a higher average educational level: 81% from that group have finished at least high school and 56% have a university degree, which is a higher value than in the overall Austrian population where 30% have finished high school and 15.7% have graduated university[32]. For people over 65, the educational level is similar in the participants of the survey and the Austrian population[32].

4.3.2 Attitude Towards Technology and AAL

94% of participants have at least slightly positive feelings towards new technology in general, out of which 34% regard it as very positive. Only one person has a very negative attitude towards new technology. All participants who rate new technology as at least slightly negative are female.
The participants rank different attributes of AAL devices according to their importance. 52% of participants regard reliability to be the most important criterion, while 94% think it is one of the three most important things (out of the six proposed). Other than that it was not possible to find a tendency of preferred ranking for other attributes (handy design, privacy protection, little installation effort, little maintenance effort, not having to think about it daily).
56% of participants have already experienced AAL devices either in their private or in their

[31] Gesundheitspersonal nach Altersgruppen, Statistisches Bundesamt Deutschland, 2016, https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Gesundheit/Gesundheitspersonal/_inhalt.html

[32] Bildung in Zahlen 2014/15 - Schlüsselindikatoren und Analysen, Statistik Austria, http://gemeindebund.at/images/uploads/downloads/2016/Statistik/bildung_in_zahlen_201415_schluesselindikatoren_und_analysen.pdf

working environment. Of these 65% had contact with fall sensors, 54% know emergency bracelets and 24% worked with intelligent light control. The major part of participants familiar with AAL (90%) has experienced these at work. Different AAL technologies are presented to the participants. They then decide about their meaningfulness. 99% regard emergency bracelets and fall sensors as meaningful, it is 96% for light control systems, 92% for medication reminder, 88% for intelligent toilets and 81% for video-telephony with doctors and relatives. The number of people considering the technology as meaningful or very meaningful is lower for the following: medication dosage (42%), watches with integrated route guidance systems (40%) and activity trackers (25%).

4.3.3 Group-specific evaluation

Table 4.8 shows factors that constitute the acceptance of AAL in general and Table 4.9 refers specifically to the acceptance of fall sensors. The variable n represents the number of participants in each sample group.

group	**n**	**PE**	**EE**	**SI**	**FC**	**HM**	**EH**	**BI**	**PC**	**DI**
users (65+)	25	75.59	66.00	44.92	71.00	63.86	4.00	21.00	59.72	72.00
nursing staff	91	75.03	95.60	43.75	57.31	68.68	42.73	43.63	56.78	70.09
relatives	36	91.50	98.62	34.72	81.42	83.34	19.39	70.13	77.78	69.19
healthcare management	33	93.80	57.58	54.54	78.10	68.18	49.19	50.86	68.68	66.41
total	185	70.81	81.08	60.27	64.86	69.46	33.51	42.97	63.97	67.84

Table 4.8: Acceptance categories for AAL in general for different user groups, given in percent

group	**n**	**PE**	**EE**	**SI**	**FC**	**HM**	**EH**	**BI**	**PC**	**DI**
users (65+)	25	70.83	66.00	45.92	71.00	51.18	0.00	8.34	59.72	72.00
nursing staff	91	81.56	95.60	59.45	57.31	68.68	74.72	62.79	56.78	70.09
relatives	36	87.30	98.62	28.13	81.42	83.34	10.56	41.95	77.78	61.19
healthcare management	33	92.24	75.76	62.12	78.10	68.18	78.45	77.42	68.68	66.41
total	185	74.59	81.08	62.70	64.86	69.46	51.08	53.24	63.97	67.84

Table 4.9: Acceptance categories for fall sensors for different user groups, given in percent

The dimensions of the applied user acceptance model used in Table 4.8 and Table 4.9 are described again in Figure 4.13.

PE	**P**erformance **E**xpectancy	the percentage of people thinking that the technology will increase their job performance, or for users, that it will facilitate things in everyday life
EE	**E**ffort **E**xpectancy	the rate of people who think it will be easy to learn the handling with the technology
SI	**S**ocial **I**nfluence	the rate of participants being influenced from other people towards using AAL technology and fall sensors
FC	**F**acilitating **C**onditions	the percentage of subjects who think of having the financial and time ressources to use those technologies
HM	**H**edonic **M**otivation	the rate of people feeling that the use of AAL or fall sensors is fun or diversifies their daily routine
EH	**E**xperience and **H**abit	the rate of participants who have already used the technology or are even used to it
BI	**B**ehavioural **I**ntention	the percentage of people thinking of using AAL and fall sensors in the future
PC	**P**rivacy **C**oncerns	the rate of attendees who feel that the benefits of AAL technology outweigh the disadvantages regarding privacy intrusion
DI	**D**esign and **I**ntegration	the percentage of people thinking it would be easy to integrate the technology in the given facilities

Figure 4.13: Description of user acceptance dimensions used in Tables 4.8 and 4.9.

Technical staff in healthcare facilities

Only 4 technicians participated in the survey. Due to insufficient representation this group is neglected for the following analysis.

End-users (aged 65 and older)

25 participants are aged 65 or older. 2 people from this group live together with family members or nursing staff because they need help in their daily routine. What can be deducted from Table 4.9 is that no participant in this group has experience with fall sensors and only 4% has already operated with AAL technology in general (see Table 4.8). 21% intend to use AAL in the future while it is 8.34% that plan on using fall sensors.

The people from this group deem the use of AAL to be more difficult than nursing staff and relatives do.

Nursing staff
41% of participating nursing staff (29 people) work in a care home, whereas 57% (40 people) work in a hospital and one person is still in school gaining experience in different facilities. 89.66% of nursing staff working in care homes have already worked or still work with AAL technology, while it is 67.50% in nursing staff working in hospitals.

Relatives
Relatives of people aged 65 and older have a high PE of AAL technology and think that using them is easy (see Table 4.8). This group has the lowest rate of SI compared with the other groups. The experience with AAL and fall sensors is higher than in the user group and lower with professional healthcare staff.

Management in healthcare facility
Participants working in management positions of healthcare facilities have a lower value for EE regarding AAL technology than all other groups (see Table 4.8), which means that they feel more that new AAL technologies imply work and effort than participants from other groups. Fall sensors are regarded to mean less effort than other AAL devices. The share of people in this group feeling socially influenced in using AAL is higher than in other groups.

AAL in general and fall sensors
Tables 4.8 and 4.9 show that the SI on health workers is higher when it comes to fall sensors than to AAL in general. For people working in healthcare management, the effort expected to accompany fall sensors is higher than with other AAL devices. Users and relatives plan to use devices detecting falls less likely than other AAL products. In contrast, nursing staff and people working in healthcare tend to think that they will use fall sensors more likely than other AAL devices.

Privacy
When speaking of GPS tracking systems, more than 77% in all groups think that the positive aspects of such a system (e.g. finding a person in case of need) outweigh the privacy intruding properties. Moreover, less than half of the participants (in people aged over 65 only 28%) regard their privacy at risk when using GPS systems. About 50% of all attendees (for nurses it is 64%), consider AAL systems using image data (not further specified into RGB, depth or infrared images) to be privacy intruding. Using a depth sensor for fall detection is regarded as at least slightly useful by 69.45% of participants.

67% of relatives, 63% of healthcare management, 48% of end-users and 45% of nurses think that the benefits outbalance the negative aspects concerning privacy. In every group except people aged 65 and older, audio tracking is regarded as intrusive by more people than when using image or video data. This accords with the findings of Hensel et al. [93] and Blasco et al. [92] that different users do not feel invaded in their privacy by the same technology. For 75% of relatives, 57% of people working in healthcare management, 52% of end-users and 45% of nurses, the advantages of such systems (e.g.

talking to a person who is unable to answer the phone) have a higher importance than the protection of privacy.

General trends
Taking the sum of all groups, 70.81% of all participants think that AAL technology will increase their job performance or facilitate things in everyday life. Nearly all health workers and relatives (95.60% and 98.62%) think that AAL systems are linked to little effort. Social influence plays a role for more than half of the attendees and is not more important for people aged above 64 than for other groups.

About two thirds of people have financial possibilities and time to use AAL technology. Approximately 70% of attendees link AAL systems with fun and diversity in everyday life or work and for relatives it is even more than 80%. Healthcare professionals have the most experience with AAL devices, while the attendees of the questionnaire aged 65 and older have almost no experience. Only 21% of end-users plan to use those systems in near future. The integration of systems in the existing facilities is regarded to be no problem for about two thirds of participants and is a greater problem when it comes to laying new floors or installing new light switches.

CHAPTER 5

Conclusion and Future Work

In this work chosen devices for fall prevention and fall detection were compared. Precision and recall were calculated to compare the products' performances. The evaluation for fall prevention devices was done in a cooperating care home with 4 participants for a period of one month. Therefore, the Bucinator Paulus, Bucinator Vivus as well as the fearless and Optex sensors were evaluated. One of each device was mounted in every room, collecting the alarm time points with a Raspberry computer and comparing them with the time points of 239 getup events extracted from depth-image-based video sequences. The assessment of devices used for fall detection was done in a laboratory setting comprising 10 subjects. Adapting existing approaches from the literature, 11 fall scenarios and 11 ADLs were set up. The iWatch4, the image-based sensor fearless, the wearable device sturzmelder and the mobile application b-cared were compared. The user acceptance for AAL devices and in particular for sensors detecting and preventing falls, was evaluated by the use of a questionnaire based on the adapted user acceptance model. 189 questionnaires were analysed, dividing the participants into the following subgroups: nursing staff, healthcare management, end-users and relatives.

The following research questions should be answered during this thesis:

- How can different AAL technologies be compared?

  The evaluation of AAL technologies focussed on fall-related devices. In order to compare fall prevention devices, the time points of getup events were extracted using a depth camera. Storing the time points of alarms sent by the different systems, the TP, FN and FP rate could be calculated. In order to test devices used for fall detection, a set of fall and ADL scenarios was used. Repeating these scenarios with a defined number of participants while having all systems installed resulted in a pool of binary data consisting of "alarmed" or "not alarmed". From that data, the recall and precision could be calculated to analyse the performance

of the tested technologies and the variations among participants.
Bucinator Paulus and fearless delivered the best getup detection results, with the Bucinator Paulus having a higher precision rate (0.85, while it is 0.68 for fearless) and fearless having a higher recall rate (0.93, while it is 0.77 for the Bucinator Paulus). In terms of fall detection, fearless outperformed the iWatch4, sturzmelder and b-cared.

- How can user acceptance of AAL technologies by different user groups be measured?

  A questionnaire was used, consisting of questions representing the acceptance dimensions of an adapted user acceptance model. 70.81% of all participants think that AAL technology will increase their job performance or facilitate things in everyday life.

- Does the impact on a patient's privacy differ between image-based and non-image-based AAL technologies?

  The perception of a device's obtrusiveness is subjective. Although researchers have made first steps towards a measurement of obtrusiveness, no metrics could be found to rate different devices. Regarding camera-based approaches, RGB, RGBD and infrared sensors have to be distinguished.
  Regarding camera-based approaches, depth and infrared sensors are considered less intrusive than RGB cameras since they hide a person's identity. Pre-processing methods using RGB cameras exist in order to apply privacy protection at the video capturing stage, while still being dependent on an algorithm's performance.

Future studies will include the target group of fall detection devices by splitting the participants into two groups: doing the fall scenarios with young and fit people like done in this thesis, and elderly people performing the ADLs. Measuring the falling speed of the attendees in the fall detection tests will help to analyse the performance of accelerometer-based devices. Attracting a higher number of elderly people in need of care to complete the questionnaire will enable the deduction of the attitude and acceptance of end-users.

CHAPTER 6

Appendix

6.1 Questionnaire

Acceptance of new technology in health care

This survey deals solely with AAL devices. **AAL** means **A**ctive **A**ssisted **L**iving and describes systems for ensuring an independent life-style especially for elderly people. An exemplary scenario is given to better illustrate the possibilities of AAL.

When Martha Williams (fictitious name) gets out of bed in the morning, the coffee machine and the water kettle begin to work and the dimmed lights in the bathroom switch on automatically. Despite the winter, the house feels cozy and warm, thanks to the heating that has already started half an hour ago. Just by pressing one switch besides the kitchen door, all the shutters go up and depending on the day time, the lights go on.

The first thing Martha does is going to the bathroom, where the toilet automatically adjusts the position to facilitate sitting down and getting up.

Martha puts the pan on the oven, switches it on and wants to take the eggs from the fridge. But she had forgotten to get some from the cellar, thus she goes down now. Since the stairs make her take a little longer, the oven switches off automatically due to the motion sensor that has not detected any movement lately.

When taking the last step of the stairs, Martha stumbles and falls. She can get up on her own and enters the kitchen, when her telephone rings. It is her daughter who has gotten a message because of the fall. Although she has also gotten the message that her mother has recovered, she wants to know if she is okay. Living one hour away, it is too far to look for her mother more than once a day. She is glad knowing about the health status of her mother despite the distance.

After the breakfast, Martha decides to take a walk. While she is lost in her thoughts, she suddenly realizes that she took the wrong turning and lost the orientation. She taps on her watch and sees that she has to go right at the next junction to get back on the track. The smartwatch could even alarm the emergency or her daughter. But on her way home, the watch just memorizes her that she still has to take her pills for today.

1. How is your attitude towards new technology in general?

   O very negative O negative O slightly negative
   O very positive O positive O slightly positive

2. Thinking of the scenario from before, and of the AAL devices that can support you or your relatives: which **demands** do you have for such a device?
   Please put the following factors in order considering their priority for you (1= most important factor)

   O Handy design (small, easy transportation)
   O Reliability
   O Privacy protection
   O Little installation effort
   O Little maintenance effort (e.g. charging)
   O Not having to think daily about it (e.g. wearing a bracelet)

3. **Do you already use AAL devices?**
   e.g. fall sensors, fall mat, emergency button/bracelet, video calls with family/doctors, intelligent toilet that helps sitting down/getting up, automatic pill dosage system, intelligent light control, watch with navigation system, activity tracker:
   O yes, namely: ______________________
   O no

4. **Which devices do you think are useful?**	Not useful at all	Not useful	Rather not useful	Rather useful	Useful	Very useful
Emergency bracelet						
Video calls with family and doctors						
Fall sensor						
Intelligent light control that turns on when detecting motion						
Intelligent toilet that helps sitting down/getting up						

Reminder for taking medicine						
Automatic medicine dosage system						
Activity tracker						
Watch with integrated navigation system						

5. Do you live together with your family or a care worker because you need **help in everyday life** or do you need this help regularly (at least once a week)?

   O Yes O No

The following questions split into one part concerning AAL technology in general and another part dealing with sensors detecting and preventing falls.

AAL in general:

- Intelligent light control
- Emergency bracelet
- Video calls with family/doctors
- Intelligent toilet/bed helping to get up
- Reminder for taking medicine

Fall sensors:

- **Fall mats/bed exit detectors**, that recognizes a person getting up from bed and automatically calls the care staff.
- **Bracelet/watch/smartphone**, that detects falls and automatically calls family members or the care staff.
- Stationary devices that e.g. detect falls by using a **camera** in order to set an alarm

	Totally disagree	Disagree	Rather disagree	Rather agree	Agree	Totally agree
The use of … would help me in my everyday life:						
AAL in general						
Fall sensor						
I think the use of … in everyday life would be/is useful:						
AAL in general						
Fall sensor						
Learning to work with the new system would be easy for me.						
I would learn to operate with the new system quickly.						
People who influence me (family, neighbours, friends, doctors,...) think that I should use AAL in my everyday life.						
People that are important to me think that I should use AAL devices.						
I have the required resources to use AAL:						
Financial resources						
Time						
I believe that I am capable of using AAL devices on my own, or that I gain support from another person.						
It is fun/it would be fun to use AAL in everyday life:						
AAL in general						
Fall sensors						

	Totally disagree	Disagree	Rather disagree	Rather agree	Agree	Totally agree
Using AAL devices in everyday life, makes it more varied:						
AAL in general						
Fall sensors						
I regularly use AAL devices in my everyday life:						
AAL in general						
Fall sensors						
I am used to using AAL devices in my everyday life:						
AAL in general						
Fall sensors						
I am planning to use AAL devices in the next 6 months:						
AAL in general, namely:						
Fall sensors, namely:						
I will try to use AAL devices in my everyday life:						
AAL in general						
Fall sensors						
I fear that AAL devices intrude on my privacy:						
GPS tracker						
Image/video data						
Automatic call by family members/care staff without having to accept (possibility to listen in)						
For me, the benefit of AAL devices overweights the intervention in my privacy:						
GPS tracker to be found in case of an emergency						
Image/video data for detecting falls						
Possibility to listen in in order to be able to speak with somebody in case of an emergency, when you are not capable of catching to the phone						

I regard the following stationary camera as useful: it detects falls and alarms relatives or nursing staff without exposing the identity of a person (only contours, no faces are visible). There is no permanent video recording, only depth images of fall events are saved.						
I have the spatial possibilities to install a new device in my house/flat:						
Bracelets/Belt clips						
Stationary sensors at home						
New floor with fall detection function						
Intelligent light control						
Daily thinking of wearing a bracelet/a clip etc. is a problem for me.						

I agree to the usage of my data for scientific reasons. All data is guaranteed to be made totally anonymous!

O Yes O No

Please enter your gender

O female O male O not specified

Please mark your highest education:

O Primary school
O Secondary school
O Apprenticeship
O Craftsman

O College
O Bachelor
O Master
O A-Levels

O Diploma
O Doctor/PhD
O Professor

In which year are you born? __________

Thank you for your participation!

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Acronyms

AAL Active Assisted Living

AALIANCE2 European Next Generation Ambient Assisted Living Innovation Alliance

ADL Activities of Daily Living

AtB Attitude towards the Behaviour

ATT Attitude Towards Technology

ATU Attitude Towards Using

BI Behavioural Intention

DI Design and Integration

EE Effort Expectancy

EH Experience and Habit

FC Facilitating Conditions

FN False Negative

FP False Positive

HM Hedonic Motivation

In Intention

IS Information Systems

PBC Perceived Behavioural Control

PC Privacy Concerns

PE Performance Expectancy

PEoU Perceived Ease of Use

PIR	Passive Infrared
PU	Perceived Usefulness
PV	Price Value
SI	Social Influence
SLM	Spatial Light Modulator
SN	Subjective Norms
TAM	Technology Acceptance Model
TN	True Negative
TP	True Positive
TPB	Theory of Planned Behaviour
TUG	Timed Up & Go
USE	Actual Use of the System
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

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