Pervasive sensing for social connectedness

Chapter 3

Pervasive sensing for social connectedness

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Abstract

Global population ageing is an emerging challenge of the twenty-first century. In an era of pervasive computing (i.e. the proliferation of ever-present smart devices), governments, companies, and academic institutions are working together to develop and promote cutting-edge initiatives that sustain the quality of life and address the complexities and opportunities of an ageing world. In this chapter, we propose a user-centred approach within a multidisciplinary framework, which incorporates human–computer interaction, social science, signal processing, and pervasive computing, to inspire the design of a bidirectional context-aware system to support social connectedness between the elderly and their caregivers. Following a review of previous works on socio-technical awareness systems and human activity recognition models, we describe our user-driven methodological approach and demonstrate the value and potential benefits of bidirectional activity-based peripheral systems within ambient assisted living environments.

3.1 Introduction

In the last century, global life expectancy has considerably increased. In 1990, the average life expectancy in the developed world was estimated between 40 and 50 years while today the predicted life expectancy is 80 years [1]. A continued rise in life expectancy will yield a major increase in old-dependency ratios, that is, the proportion of elderly persons not in the labour force to those of working age [2]. Following this trend, the World Health Organization predicts that the number of persons aged 60 and over will be more than double its size going from 901 million in 2015 to nearly 2.1 billion in 2050 [3]. This unprecedented phenomenon is driven

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by improved nutrition, access to sanitation, increased access to education and advances in medicine, primarily in the diagnosis and treatment of diseases [1]. Although this is a sign of progress, there are many concerns associated with population ageing, which are yet to be addressed.

Primarily, population ageing can impose considerable economic cost and social implications. These include increased government spending on health and long-term care, the shortage of formal caregivers (e.g. nurses/care-home personnel), and increased taxation for the working-age population to support pension schemes. Moreover, population ageing imposes pressure on informal caregivers (e.g. family/friends/neighbours living apart, who maintain social contact with the elderly once or twice per week) trying to strike a balance between the responsibility of taking care of their elderly loved ones and their own personal and professional lives.

3.1.1 Social isolation and loneliness as risk factors

With respect to social implications, some researchers believe that social isolation and loneliness are affiliated with old age [4,5]. Social isolation is identifiable by a wide range of indicators, namely living alone, having little or no social participation, perceived lack of social support, and feelings of loneliness. Some gerontological studies suggest that social isolation and loneliness have precarious health risks commensurable with smoking and obesity in older adults [6]. In fact, social isolation has often been held accountable for increased mortality in older adults [6,7].

Besides social isolation and loneliness, increased longevity is associated with heightened susceptibility to several medical issues, including cognitive disorders, cardiovascular and mental health diseases, and motor and physical disabilities [7,8]. Despite the elderly's increased vulnerability to social isolation, chronic illnesses and disabilities, the majority are in favour of living independently and remaining in the comfort of their own homes [9], a concept more formally coined as *ageing in place* [10]. However, many homes in their current state are unfit for accommodating the mobility limitations of older adults. Thus, prompting the demand for safer, smarter, and more adaptable homes. To address these challenges, both public and informal care services are searching for assistive living solutions that enable sustained well-being and independent living while simultaneously lowering the costs associated with elderly care. For example, the National Foundation for the Elderly[1] is a Dutch charity organization, which aims to promote quality of life and prevent isolation among older adults.

3.1.2 Ambient assisted living

With the goal of meeting the day-to-day needs of older adults, ambient assisted living (AAL)[2] is an interdisciplinary field which aspires to develop innovative technical solutions for preserving health, functional independence, and enhancing

[1] https://www.ouderenfonds.nl/
[2] http://www.aal-europe.eu/about/

social interaction among older adults. Ambient intelligence (AmI), the backbone of AAL, aspires to detect people's state and adaptively respond to their needs and behaviours through the integration of ubiquitous technologies in their environment [11]. Drawing from disciplines such as artificial intelligence, human–computer interaction, pervasive/ubiquitous computing and computer networks, AmI systems can sense, reason, and adapt to offer personalized services based on the user's context, intentions, and emotions [12,13]. In this way, such systems, also known as context-aware systems [14], can be integrated into AAL environments to provide better care and support for the elderly living independently.

To provide context awareness, safety and autonomy, a wide array of applications are geared towards remote monitoring, indoor localization, fall risk assessment, and fall detection to notify caregivers and emergency services of anomalous occurrences in the homes of the elderly [15]. In particular, monitoring activities of daily living (ADL) [16] are critical to determining the elderly's functional mobility and their competence to live independently. As a result, human activity recognition (HAR) has become a critical feature of AAL, to support motion detection and physical activity monitoring.

Although AAL technology has provided overarching benefits through enhanced personal assistance, prolonged independent living, and improved quality of life, there are some open research problems in need of further exploration by the AAL community. Firstly, most conventional AAL tools are intended for emergency/anomaly detection [15] with limited motivation towards improving social connectedness, that is, 'the experience of belonging and relatedness between people' [17]. Secondly, progress in understanding the nature of the users in their physical environments, their dynamic needs and expectations is challenged by readily available computer simulation tools, which often ignore the real challenges (cognitive impairments, motor and physical disabilities, social isolation and loneliness) faced by the ageing population. Thirdly, existing AAL solutions are usually one-sided (i.e. only providing contextual information to caregivers), resulting in concerns with respect to the invasion of the privacy [18,19] of older adults. Overall, most AAL practitioners when addressing the design and validation of AAL solutions are ostensibly more focused on technical features and functionality to support the frailty of the elderly at the expense of designing to ensure that products are acceptable and beneficial to both the elderly and their caregivers.

Towards this end, we argue for a user-centred approach to the design and development of a bidirectional AAL solution to support social connectedness through the mutual awareness of activity levels between the elderly and their caregivers. Consequently, the chapter explores the idea of active user participation in the design and evaluation of a bidirectional activity-based ambient display platform geared towards improving social connectedness in AAL environments. In the following sections, we provide evidence for the following claims: (1) a user-centred approach is necessary to design AAL systems for social support, (2) robust and reliable classification algorithms are essential for awareness systems within AAL, and (3) bidirectional ambient displays deployed within an AAL framework can enhance social connectedness.

3.2 A user-centred approach for designing systems to support social connectedness

Don Norman, a pioneer in user-centred design, highlights the importance of understanding human behaviour to affect technological designs positively [20]. He further argues that people are not responsible for the complexities that arise from the use of technology, but instead can be largely determined by the technology itself. Quite often, we see this translated into the design and development of interactive technologies for older adults, such that solutions are far more *data centric* rather than *user supportive*.

User-centred design is a human-centred process, with a primary focus on users and their tasks, paying keen attention to an empirical assessment of adoption and technology use, while predominantly deploying an iterative design approach, whereby a product is designed, modified, and repeatedly tested [21]. Thus, from the very onset, both designers and engineers need to establish an explicit understanding of the users' context, tasks, values, needs, and expectations from the users' perspective. As a consequence, researchers can gain deeper insights into future usage scenarios to tailor solutions, which can be incorporated into the users' daily practice and environments.

When designing for social interaction within an AAL context, there are two user groups to be considered, that is, the elderly and their caregivers, whether familial or professional. Notably, each constituent group has its own needs, preferences, and expectations. In particular, older adults are extremely diverse, with multifarious differences in terms of physical and cognitive abilities, societal values, social networks, religious beliefs, living arrangements, and technological expertise and acceptance. On the other hand, younger adults are in general more abreast with technology, tend to have busy lifestyles, and often struggle with the responsibility of caring for older adults. Accordingly, these factors should be taken into account when designing holistic technological tools to support the needs of all AAL stakeholders.

Participatory design is a human-centred approach, whereby users are involved in the conception, design, and development of products [22]. Traditionally, participatory design methods include but are not limited to the following classical ethnographic-based techniques: (1) on-site observations, (2) audio and video recordings, (3) self-report questionnaires, (4) in-depth interviews, (5) contextual inquiries, (6) surveys, (7) focus groups, (8) note-taking, (9) artefact analysis, and (10) diary collection [23].

The contextual inquiry, a mixture of interviewing and observation techniques deployed with real users in their natural environments, is an invaluable tool for soliciting user requirements for existing and potential product use [24]. In fact, the contextual inquiry is known to reveal the *invisible* details of the stakeholder's environment and is viewed as an enabler for co-design and creating stronger collaborations between the users and designers [24].

Within AAL, the potential incapacity of older adults to understand the fundamental concepts of novel ambient technologies could hinder their imagination and acceptance of such systems [25,26]. Thus, providing more contemporary participatory design techniques, such as those based on theatrics [25] or storytelling principles notably, co-constructing stories [27], could be beneficial to help older adults imagine user requirements and envision future usage possibilities.

As the design cycle evolves, participatory design techniques such as low-fidelity mock-ups and prototyping could be helpful to designers to discover measurable user experiences and usability criteria [28]. These include but are not limited to the following criteria: (1) ease of use, (2) effectiveness, (3) efficiency, (4) safety, (5) pleasure, (6) utility, (7) attention, (8) learnability, and (9) memorability [28,29]. At this point, the potential problems can be identified, thus prompting further redesign to ensure that the system addresses the stakeholders' needs.

In summary, by paying close attention to the aforementioned user-centred design approaches, it is possible to deploy a set of participatory design techniques to infer user requirements and gather rich qualitative data on usability experiences of both the elderly and their caregivers in order to develop systems to support social connectedness. In the next subsection, we put these techniques into action.

3.2.1 A user-centred design process

To properly understand the needs and values of users and to place users in the centre of the design process, a domain and requirements analysis phase and a system design and validation phase are incorporated in our design approach, as illustrated in Figure 3.1. In this work, the co-constructing story [27] is used to sensitize the users to the social isolation problem (through the sensitizing story) and to help both the elderly and their caregivers imagine the user requirements of the system and to envision future usage possibilities (via the elaboration phase). A typical sensitizing story can be illustrated as follows [30].

> Mrs. Audria Visser is a retired 75-year-old store keeper who lives independently in an elderly apartment in Eindhoven, The Netherlands. Her husband, Mr. Roy, Visser, died 5 years ago. Mrs. Visser's only child, Steven Visser, is 45 years old and is a software developer in Groningen. He is married to Tamoi Visser with children Elizabeth and Jonathan, 8 and 13 years, respectively. Mrs. Visser suffers from mild hypertension and has biweekly visits from the doctor. She cooks, cleans, goes grocery shopping, and occasionally does her own gardening. Mrs. Visser's social ties include her neighbours, her church family members and her lifelong friend, Mrs. Karole Abbes, who lives in a neighbouring community. Moreover, she is in contact with her sister, Ms. Cheryl Aarts, and her son, Steven, and his family. Mrs. Visser keeps in touch with her family via the telephone and has irregular visits from Cheryl and Karole. Distance and high job demands have restricted regular visits from Steven and his family limiting them to telephone conversations 1–2 times per week. Steven is worried about his mother's psychological and physiological well-being and desires to be more aware of her activities. Although his mother's hypertension is seemingly controlled, Steven is fearful that she lives alone and would like to be informed in the case of eventualities.

The sensitizing story was beneficial for sensitizing users to the ageing problem, promoting reflection, and determining how users identified with the

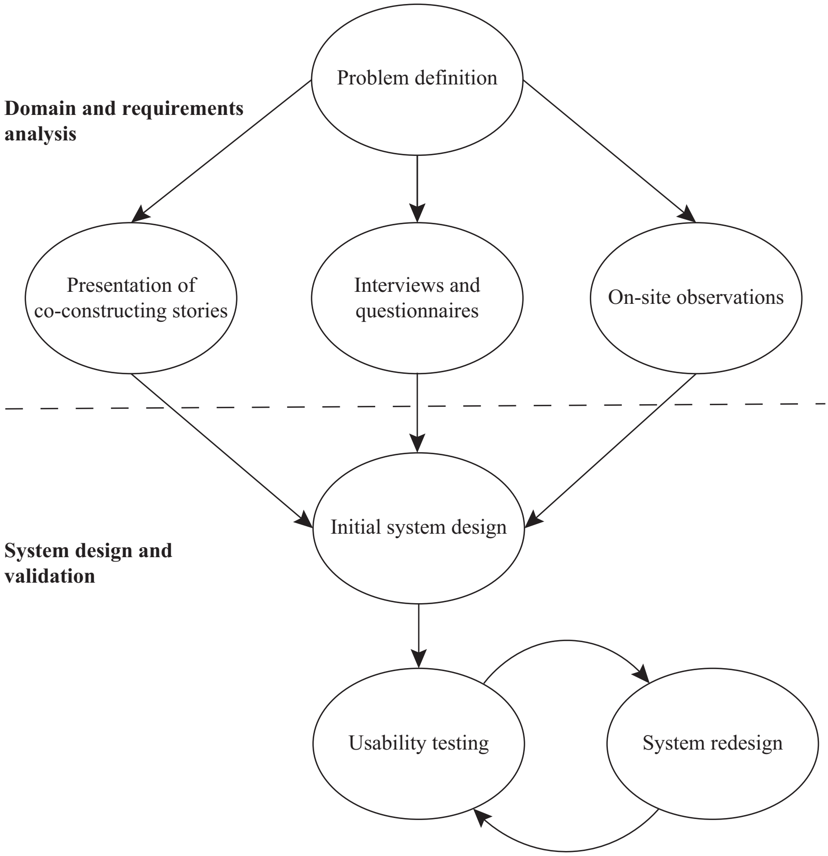

Figure 3.1 A user-centred design process

characters. Thereafter, during the elaboration phase, participants viewed service design images of the proposed technology, which led to active discussions on their acceptance of wearable devices and ambient displays for enabling context awareness and improving social connectedness.

To further gain a deeper understanding of the users in context and to measure the effect of proposed context-aware connectedness solutions, on-site observation and a number of quantitative measures are deployed to assess the elderly's independent living skills, perceived isolation (subjective feelings of loneliness), relationship closeness, and social presence/connectedness.

- Functional ability and independent living skills: This investigation is done to assess an older adult's functional abilities and their instrumental activities of daily living (IADL), that is, the skills needed for living independently (e.g. housework, laundering, and meal preparation). The Lawton IADL scale [31] is a standard instrument for measuring self-care and is well-validated in geriatric communities [32]. It consists of eight IADL items assessing the degree of dependence in telephone use, mobility, grocery shopping, meal preparation, housekeeping, laundry, medication and financial management. Within AAL, the results of an IADL assessment may serve as an early indicator of functional decline [31].

- Perceived isolation: The UCLA loneliness scale [33] is widely recognized as the *gold standard* for measuring subjective feelings of loneliness and social isolation. It comprises 20 items, examining the rate of reoccurrence of feelings of being alone and misunderstood, lack of companionship, social inclusion, and relationship closeness. Every item is followed by a four-point Likert scale ranging from 1 = never to 4 = always. In this chapter, our evaluation of the UCLA loneliness scale is inspired by the view that social isolation and loneliness are objective indicators of the extent to which a person is socially connected [34].
- Perceived relationship closeness: Within this research, we are motivated to understand the social relationship between the elderly and their caregivers. The instrument, the Inclusion of Other in the Self Scale developed by Aron *et al.* [35], is one of the most highly cited measures of the perceived closeness of relationships. It consists of a seven-point pictorial scale using two overlapping circles, whereby a closer intersection indicates stronger sentiments of love and companionship.
- Perceived social presence: Although social connectedness and social presence are closely related, they are not the same. In fact, Ijsselstein *et al.* suggest that these two concepts are complementary, alluding to stronger feelings of social connectedness complemented with lower levels of social presence, regarding awareness systems [36]. Accordingly, the Institute for Perception Social Presence Questionnaire [36,37] was developed to focus more on measuring the affective benefits (i.e. ‘a feeling of having company, a stronger group attraction, a feeling of staying in touch, of keeping up-to-date with other people’s lives, and a sense of sharing, belonging, and intimacy’) of awareness systems.

Based on the outcome of the initial system requirement analysis, the system design and validation enters into an iterative process where perceptions of users regarding ease of use, privacy, usefulness, and the perceived effects of the initial system are taken into account in subsequent system redesigns. This ensures that much importance is given to user feedback in the design of the system’s functionality.

3.3 Context-aware systems for social connectedness

Mark Weiser’s seminal work [38], *The Computer for the 21st Century,* described his vision for ubiquitous computing. In his narrative, Weiser imagined a world where technology would silently reside in the background or periphery of the user’s attention, is available at a glance, when needed. As such, the minimum allocation of attentional resources would enable peripheral interaction with a system as suggested in the statement: ‘The most profound technologies are those that disappear.

They weave themselves into the fabric of everyday life until they are indistinguishable from it' [38]. To this end, ubiquitous computing aims to enable calm technology [39], whereby information is easily transported between the centre and periphery of attention.

The notion of context-aware computing [14], the adaption of a system's behaviour in response to the sensed physical environment, is therefore, a derivative of Weiser's vision of ubiquitous computing. Though earlier research on context-aware computing was more focused on location-aware applications and remote monitoring for fall detection, the domain is evolving also to support interpersonal awareness between the elderly and their caregivers within AAL.

As mentioned earlier, context awareness is a central theme in the field of AmI, and as such, it is of paramount importance to facilitate the sharing of health and well-being information between remote caregivers and their elderly relatives. This information may be provided through direct notifications to users or within the periphery of their attention.

To achieve the latter, ambient displays, a sub-discipline of AmI, are used to portray representations of contextual information in the periphery of users' attention [40]. By deploying ambient displays, information can be presented through stand-alone or a combination of visual, audio, or tactile modalities, without being distracting. Within the AAL domain, a number of studies have demonstrated benefits of ambient displays to enable contextual awareness and strengthen social interaction.

The Digital Family Portrait [41,42] is a prototypical example providing substantive evidence of the use of ambient displays for enabling peace of mind of remote family members worried about their elderly relatives living independently. To illustrate a qualitative sense of a senior's daily activities, location and activity information are rendered to a caregiver using a photo frame. The results of the field trial between an elderly mother and her adult son attest to the caregiver's appreciation of the system's monitoring capabilities for detecting unusual events, while not raising privacy concerns for the elderly parent. At the same time, the elderly parent expressed satisfaction with the system, emphasizing that the notion of someone *looking in* made her feel *less lonely*.

Similarly, visual-based studies such as the Carenet Display [43], Aurama [44,45] (both augmented picture frames, built upon information received from sensing devices), Daily Activities Diarist [46] (the narrative presentation of the elderly's routines) and MarkerClock [47] (facilitates the sharing of activity information through a clock) rely on the automated capture and display of elderly contextual information for enabling remote monitoring, and supporting connectedness and peace of mind of caregivers.

Other systems such as the Whereabouts clock [48] enable the exchange of location information by exploiting everyday devices such as a clock and the smartphone. Placed in the home, for example, in the kitchen or living room, users can explicitly receive information regarding their family member's location such as (*home, work, school*). The qualitative results of a longitudinal study suggested affective benefits of the system while it simultaneously provided a sense of connectedness and reassurance to family members, confirming the normality of the other person's situation.

On the other hand, ambient displays supporting tangible interaction include the Lumitouch lamp [49] and SnowGlobe [50], to support the virtual exchange of social gestures, for example, using touch or a nudge to communicate affection and facilitate remote presence. For example, the Lumitouch lamp [49] conveys emotional information through a picture frame using light patterns, such that a glow is reflected when the other lamp is touched. In a similar design, the Snowglobe lamp [50] exploits features such as brightness to show a remote person's movement. Additionally, users can virtually exchange social gestures by shaking the device. Most of these systems provide a context information in one direction from the elderly to the caregiver which raises trust and privacy concerns. Also, the process by which some of these systems extract meaning (e.g. human activity patterns) from complex sensor data is not clearly explained, and therefore, it becomes difficult to argue their reliability. Subsequent sections address these issues.

3.4 Pervasive sensing and models for HAR

Human activity patterns can convey a wealth of information with respect to health, moods, and behaviour. Within the AAL domain, the monitoring of ADLs, for example, bathing, dressing, housekeeping, and food preparation, is essential for explicitly exploring the physical activity patterns for sustaining autonomy and quality of life among older adults. In addition, ADL monitoring can facilitate early diagnosis of a variety of diseases, including Alzheimer's [2,51,52], Parkinson's [53], and Dementia [2,54], and in turn, divulge reliable information concerning an elder's ability to live on their own.

Since the manual assessment of ADLs is largely impractical within this context [2], there is the need for automatic recognition of physical activities – generally known as HAR. Common activities typically exploited include walking, walking upstairs and downstairs, sitting, standing, and laying [55–57].

A smart home, commonly defined as a residential facility, augmented with technology to provide comfort, energy efficiency, and safety to its occupants [2,58], is a test bed for analysing HAR models. Within AAL, smart homes have been utilized to assess the psychological and physical health of its occupants. For instance, Cook *et al.*, through the CASAS project, employed machine learning algorithms to support remote health monitoring of the elderly [59].

Within a smart home, sensors initiate the data acquisition process by gathering data on ADLs, so that signal processing algorithms can learn and make inferences from the data. A variety of sensing devices have been deployed to facilitate HAR. These include accelerometers, gyroscopes, and global positioning system (GPS), magnetometers, radio frequency identification (RFID), and microphones to detect changes in location and movement [2,60]. Moreover, emerging trends in recent research show that accelerometers have been combined with gyroscopes and magnetometers to improve recognition performance [61].

Sensing technologies can be categorized into two groups: non-wearable and wearable sensors. Non-wearable sensing devices are usually installed in stationary locations of the smart home. This is done to predict changes in location, gait and activity patterns [2,53]. Within AAL, examples of non-wearable sensing technologies for ADL classification include infrared (PIR) sensors for motion and human presence detection [62], vibration sensors for fall detection [63], pressure sensors for detecting human presence and falls [64], cameras for activity recognition [65], and audio sensors for detecting door opening and closing [66]. Based on the reports in [67], the use of camera-based monitoring might not be applicable in AAL due to greater concerns towards the privacy constraints.

On the other hand, wearable sensors are body-worn devices, which enable the collection of context data by embedding electronic technology into everyday objects (e.g. watches, smartphones, jewellery, or clothing) to measure motion or physiological characteristics, for example, blood glucose, blood pressure, and cardiac activity [2,58]. Within the AAL domain, wearable sensors are in most cases used for ADL monitoring and classification. Primarily, wrist-worn sensors including wristwatches, bracelets, and magnetic sensors are used for activity recognition [2]. Although wearable sensors have shown much potential for ADL monitoring, they are often sold at exorbitant cost and are frequently challenged by their privacy and security vulnerabilities.

Remarkably, the smartphone is comparable to hand-worn sensing devices for enabling HAR. Housing a myriad of miniature sensors, for example, accelerometer, gyroscope, GPS, magnetometer and a microphone, the smartphone is capable of supporting the acquisition of rich data sets as demonstrated in [2,56,57,68]. Moreover, it is equipped with a variety of components including Wi-Fi, 3G/4G, and Bluetooth, which enables communication with other services.

Although smartphones offer great potential for HAR, there are some hardware-related challenges, such as battery life, processing power, and memory capacity constraints [56]. Thus, it might be challenging to compute resource-intensive machine learning algorithms on smartphones [61]. This problem can however be overcome by using the smartphone only for sensor data collection and then performing other HAR resource-intensive tasks on a remote server. Also, the smartphone's portability, affordable cost, and ubiquity make it ideal for supporting the convenient, continuous, and unobtrusive monitoring of physical activities, without imposing many restrictions in one's home [69]. For example, Dai *et al.* [70] developed a fall detection system using the inbuilt smartphone accelerometer. Moreover, our proposed HAR hybrid model [56] advocates the use of the smartphone, placed on users' belts for sensor data collection.

To facilitate the successful adoption of pervasive sensing technologies in AAL, user comfort with respect to the amount and location of deployed sensors must be carefully considered as it directly affects the acceptance of the system [60]. In fact, sensors placed in certain positions or deployed in multiple locations might negatively influence the users' ability to perform activities normally and comfortably within AAL.

Also, HAR models used in AAL should be accurate and reliable to prevent misdetection and false alarms as false positives may cause excessive anxiety and result in unnecessary worrying, especially for caregivers. Therefore, the need arises for being able to explore very accurate HAR models suitable for deployment within AAL.

There is a wide spectrum of approaches towards sensor-based human activity classification and recognition ranging from simple pattern recognition models, for example, threshold-based classification methods [71], to more advanced machine learning classification models. The most common models employ supervised learning techniques [72], conditional random field [73], rule-based reasoning [74], artificial neural networks (ANNs) [75], and probabilistic modelling [76,77]. Also, unsupervised learning methods have been proposed for HAR [78].

Although these methods have shown progress in the field of sensor-based activity recognition, it has been difficult to achieve very high accuracies within the AAL domain due to these challenges:

- The inconsistency of ADLs, that is, different people perform activities in different ways and in different sequences [56,79].
- Sensor data tend to be noisy or ambiguous, thereby affecting classification results [56].
- A large majority of previous activity recognition experiments were conducted using data from relativity young people. This data might not be truly representative of activity characteristics of older adults [60].

Notwithstanding these challenges, generative models have been reported to successfully handle these uncertainties [80]. Generative models estimate the joint probabilities of observed samples, which are used to predict the likelihood of a class to which a new sample belongs. More importantly, hidden Markov models (HMMs) have shown solid potential for addressing the ambiguities of interpretation within the AAL domain [76]. HMMs are mostly useful for activity recognition by virtue of their ability to exploit the temporal and sequential characteristics of activity data, thereby enabling the prediction of future states from current observation data. Though HMMs have demonstrated notable success, they are not without limitations [81]. To begin with, they struggle in representing concurrent or interleaved activities, which can be problematic when modelling continuous activities which occur in the AAL domain. Second, their strict independence assumptions make them inadequate for the capturing of transitive dependencies of observations. Moreover, it is not feasible to model the feature vector extracted from accelerometer and gyroscope sensors.

As opposed to generative models, discriminative models estimate the conditional probability distribution of labelled sequences from the observations. A feasible solution to overcome the shortcomings of HMMs is to use a discriminative model such as the support vector machine (SVM) to determine the emission probabilities of an HMM, which can then be combined with the dynamic temporal features of the HMM to give improved classification accuracy. In particular, it has been demonstrated that the hybrid SVM-HMM model achieves better performance when contrasted with stand-alone SVM and ANN classifiers [82]. Nonetheless, this improvement in recognition accuracy was achieved using a network of binary sensors, which is different from the goal of deploying as few sensors as possible. In addition, the method used for data collection was quite invasive as participants wore many wearable sensors on various parts of the body including the thigh, both wrists, and neck. For user comfort, in this work, we advocate the deployment of as little sensors as possible for activity recognition. Taking advantage of the powerful in-built sensors of the smartphone and the complimenting potentials of SVM and HMM, we developed and evaluated a hybrid SVM-HMM model for detecting six basic activities (standing, sitting, walking, walking upstairs and downstairs, and laying) within AAL.

3.5 A case study evaluating the HMM-SVM model

To overcome the drawbacks of generative and discriminative models, we combined a multi-class SVM model and an HMM into a single hybrid model [56]. The standard multi-class SVM model employs one of the two strategies: (1) a one-against-all strategy in which one SVM is used for each class and (2) a one-against-one strategy in which an SVM is used for each pair of classes. The one-against-all strategy, which has shown better results for multi-class classification problems [83], is used here. The one-against-all strategy consists of building k number of SVM models and then training the ith model, where $i \in k$, with data samples belonging to class i as positive samples and all others as negative samples. The classification of samples is therefore formulated using winner-takes-all approach [84] given by (3.1), where f_i is the ith model.

$$f(x) = \text{argmax}_i f_i(x) \tag{3.1}$$

HMM, on the other hand, seeks to infer hidden states from observed data samples. The first-order HMM shown in Figure 3.2 consists of a hidden state vector $x_0, \ldots, x_k, \ldots$ and an observation vector $y_1, \ldots, y_k, \ldots$ where the observation vector represents quantities that can be measured by sensors or derived from sensor data deterministically while the state vector represents the corresponding class labels which must be inferred.

HMM is characterized with two conditional probability density functions: (1) $p(x_k|x_{k-1})$ depicted as horizontal arrows in Figure 3.2, which is referred to as the state transition model and (2) $p(y_k|x_k)$ represented with vertical arrows in

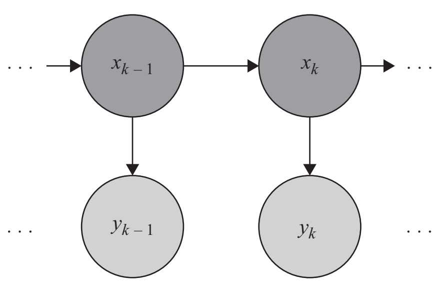

Figure 3.2 Hidden Markov model ©IEEE. Reprinted with permission from [56]

Figure 3.2, which is called the emission model. Note that the standard multi-class SVM is a discriminative model and therefore, does not generate the conditional probabilities used by the HMM. However, simple post-processing can map the output of the SVM to these conditional probabilities also known as posterior probabilities. Having calculated the posterior probabilities, the activity class is obtained as the maximum a posteriori state [56,85].

In order to evaluate the accuracy of the developed hybrid model, we collected 5,744 accelerometer and gyroscope data samples using a similar approach adopted in [86] where participants wore a waist-mounted smartphone around their waist to perform the six basic activities (standing, sitting, laying, walking, walking upstairs and downstairs). Each activity was performed for exactly 1 min. Figure 3.3 shows a participant performing the *walking upstairs* activity.

Each data sample was represented by 561 features extracted from the accelerometer and gyroscope on a fixed length sliding window of 2.56 seconds (s) with a 50% overlap. The feature vector consisted of statistical measures (mean, standard deviation, etc.) of the jerk of the angular velocity, body and gravitational acceleration [56,83].

Figure 3.3 A participant with a waist-mounted phone for data collection ©ACM. Reprinted with permission from [69]

The initial 5,744 data samples were obtained from 31 healthy volunteers within the age range of 22–79 [56], thereby providing varied samples with respect to gait. Also, each activity was performed in the homes and workplaces of the volunteers, thereby providing varied samples with respect to staircase structure. To increase the size of our data samples and to reduce the biases within our own data set, we merged the collected data set with the publicly available data set [86], whose collection approach we adopted. Xiangxin *et al*. [87] emphasized that the need for large and varied data sets for training classification models is as equally important as the need for more complex models. In total, we obtained 16,043 data samples for training, cross-validating and testing the hybrid SVM-HMM model [56].

To determine the classification accuracy of the hybrid model, we applied the famous 10-fold cross-validation [88] technique where the total data set was divided into 10-folds, and 9 out of the 10 parts of the data was used for training, and one part was held out for testing in each cross-validation phase. The overall accuracy obtained was 99.7% [56]. To compare the obtained accuracy with the performance of other classifiers, we trained and tested a stand-alone multi-class SVM model [83] and a standard ANN model in a similar way on the data set [56]. The overall accuracies obtained were 97.6% and 91.4% for the multi-class SVM and the ANN, respectively.

3.6 Context-aware connectedness systems

Even though earlier connectedness-oriented systems (Digital Family Portrait, CareNet, Diarist, etc.), demonstrated promising early results on aspects of connectedness, for example, sentiments of safety and reassurance, there is a lack of empirical evidence surrounding an understanding of the needs, acceptance, and perceptions of the elderly and their caregivers. In particular, these studies lacked the relevant measurement instruments to quantitatively assess or objectively quantify the user experience. In addition, only a few systems were evaluated in a real-life context or for an extended period. Thus, warranting further confirmation through an increased number of participants and longer trial durations.

In addition to the level of user acceptance, earlier connectedness-oriented systems were in most cases unidirectional. Generally speaking, the elderly party was mainly observed to determine situational awareness, for example, daily routines, medications, or anomaly cases while the caregiver acted as an *observer*, to provide care and support when needed, while simultaneously gaining a peripheral sense that everything is happening as anticipated with their elderly counterpart. This unbalanced communication channel could have considerable privacy implications especially with respect to the violations of privacy and dignity rights for the elderly. On the contrary, in cases where bidirectional deployment was attempted, it was difficult to obtain equal acceptance of the system. This was evident in the Aurama display [45], whereby the elderly were allowed to marginally inspect the caregiver's information while the caregiver was capable of observing more details with respect to their elderly loved one. Overall, bidirectionality was not equally supported or appreciated as caregivers were more accepting of this feature while the elderly believed it was more relevant to caregivers.

From the literature review, a considerable number of connectedness-oriented studies assessed the elderly's ADLs by deploying sensors in and around the home. However, the number and type of sensors deployed were too many and in some cases obtrusive. Specifically, the Digital Family Portrait [42] deployed a wide array of 16 sensors ranging from wearable RFID tags to wireless motion detectors. In hindsight, noisy signals and instability of the detection field with respect to motion sensors were some of the issues raised by Rowan in his Digital Family Portrait study. Also, in some instances, the use of intrusive camera-based sensing to support activity recognition was observed, for example, in [89]. Consequently, prompting the need for gerontological studies to provide motion sensing technologies that provide long-term detection stability and noise reduction while simultaneously respecting the elderly's privacy needs by avoiding camera-based sensing technologies and deploying as little sensors as possible.

Due to the emphasis placed on sustaining the elderly's health within AAL, careful consideration should be given to the accuracy and reliability of the sensing infrastructure and by extension the overall system performance. This is necessary to build system trust, guarantee the authenticity, and validity of the information received, and thwart undue stress on the part of the caregiver. It should be noted that earlier deployments of connectedness-oriented systems suffer from limitations surrounding the reliability and accuracy regarding the interpretations of the sensed data. For example, in the case of the Diarist [46], an erroneous system caused regular misdetection, resulting in needless distress for the caregiver. Also, with respect to system performance, to the best of our knowledge, only one connectedness-oriented system minimally discussed their activity recognition approach and its performance. In fact, overall system accuracy reported was 73%, which is moderately low for an AAL context. Considering the shortcomings of the previous connectedness-oriented systems in AAL, we propose the next generation of systems and research aimed to

- Provide a holistic understanding of the users' context, their needs, perceptions, and insights relating to context-aware connectedness-oriented technologies in AAL.
- Maximize on the opportunistic sensing capabilities of the smartphone in an effort to avoid intrusive camera-based sensing and to deploy as little sensors as possible.
- Provide a more robust and accurate activity recognition approach for connectedness-oriented systems to better support a realistic representation of the users' context in AAL.
- Encourage equal communication and acceptance in both directions via a bidirectional human activity-based ambient display to improve social connectedness and context awareness between the elderly and their caregivers. This bidirectional system is illustrated in Figure 3.4 and discussed in the rest of this section.

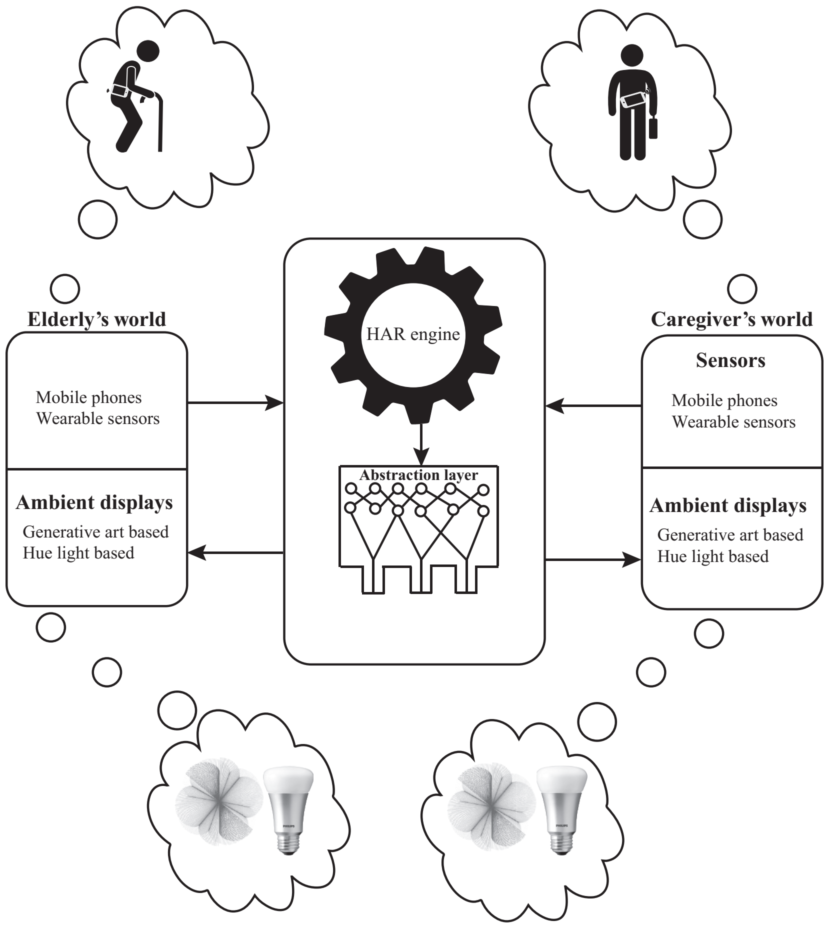

Figure 3.4 Bidirectional activity-aware system for improving social connectedness

The proposed bidirectional connectedness system comprised four main components:

- Wearable sensors (smartphones): These collect activity information by means of their in-built accelerometer and gyroscope sensors and actively send this information to the HAR server/engine. With modern smartphones' high computing power, some simple pre-processing (e.g. cleaning of the data) can already be performed by the phone before the data is sent to the server. Note that the desired context information in this setup is the human activity information.
- An HAR engine: This receives sensor data from the wearable mobile phones, extracts 561 features from every 2.56 s of data with a 50% window overlap [83] and applies the trained HAR model to detect the activities performed in each window.

- To protect users' privacy and to engage the minds of the elderly for introspection, the actual detected activities (walking, standing, etc.) are abstracted into activity levels (low or high) according to user-defined mappings between basic activities and activity levels [69]. Users are made to define activity levels, based on their work, time of day, mobility, and the basic activities they deem low or high. These maps are used by the abstraction layer to transform the outputs of the HAR classifier into activity levels, which in turn serves as input to the ambient displays.
- Ambient displays: These may be projected with a hue lamp or a computer-based visualization, which renders the received activity information based on predefined patterns of light, colour, motion, and speed.

In essence, equal complexity and detail of information is bidirectionally shared between caregivers and their elderly counterparts alleviating the fear of privacy invasion, which is usually expressed in unidirectional connectedness systems where only the elderly's activity information is shared with the caregivers.

3.7 Experimental results

Adopting the proposed user-centred approach in designing bidirectional context-aware systems for social connectedness, two studies have been undertaken to explore the perceptions of the elderly and their caregivers on context-aware solutions, and to also evaluate an initial design of an activity-based context-aware system for promoting social connectedness.

3.7.1 Perceptions on context-aware solutions for social connectedness

This experiment introduces the preliminary phase towards a user-centred approach to designing context-aware solutions for social connectedness between the elderly and their caregivers. Over a period of 3 months, 10 caregivers and 10 senior citizens, contacted through personal networks and house-to-house recruitment, participated in an exploratory study [30]. In terms of demographic data, participants were highly educated and were primarily from Western Europe with one exception from Canada. The co-constructing stories technique [27], accompanied by in-depth interviews, observations and service images, was deployed to collect in situ data from participants. Questions regarding the user's context (social ties, loneliness situation, social engagement, and the frequency of contact with loved ones), perspectives on pervasive sensing (sharing and receiving physiological information, and relevance) and preferences (wearable sensors, ambient lighting characteristics, and privacy and control) were investigated. A thematic analysis [90] was performed to analyse the data.

With respect to the social environment, the loneliness levels of the elderly participants were much lower than anticipated [30]. Nonetheless, a few elderly respondents admitted to perceived loneliness tendencies and one participant highlighted his dependence on assistive technologies to sustain his independence. Scepticism regarding the deployment of wearable sensors was initially evident among a few participants. This was mainly due to the privacy issues associated with sensor deployment (e.g. obtrusiveness of the sensors and ethical concerns surrounding the sharing of physiological information) [30]. Also, some participants felt that sensors for elderly safety monitoring were more appropriate for the frail elderly population. In keeping with Weiser's vision of ubiquitous technology [38], participants requested an 'invisible' form of technology, whereby the wearing of the device would evade conscious attention. Thus, participants generally endorsed wearable smart watches, jewellery and undergarments for their subtlety and unobtrusiveness.

Participants generally reported a positive attitude towards ambient lighting displays for social connectedness in AAL [30]. Accuracy and reliability of the context information, aesthetics, and subtlety were some of the features articulated during the requirements-gathering phase. Warmer lighting colour temperatures for presenting context information were generally agreed to evoke positive moods and trigger past memories of interactions with loved ones. Moreover, participants largely preferred customisable colour options based on context and personal preference. On the other hand, a few elderly participants raised concerns at the use of ambient technologies to enhance social relationships. One elderly participant emphasized that in order to improve social connectedness among older adults and their relatives one has to first strengthen their communication with them instead of using only technology as a means to improve the interaction. Therefore, technology should support interpersonal interactions and should not be used to replace personal interaction in AAL. Table 3.1 gives a summary of the themes that arose from the study [30].

3.7.2 HAR-based activity displays for social connectedness

In a second experiment, we exemplified a user-centred approach through the design and evaluation of a human-activity-based display for social connectedness [69]. The main objective of this study was to assess the social connectedness implications of the deployment of a bidirectional physical activity-based ambient display in the users' home and/or work context. In addition, indicators such as functional ability, loneliness, and relationship closeness were also studied. Finally, the value of the system was explored to describe the participants' experience in terms of social presence, with a focus on the affective benefits of the system. Design guidelines were acquired from a heuristic evaluation with six usability specialists, who compared an animated curve stitching pattern against regular pulse waves for showing activity data. The animated curve stitching pattern was largely preferred in the expert analysis and was later used to design the ambient display.

A usability study was conducted in Canada, with six elderly–caregiver pairs [69]. Caregivers were between 49 and 58 years while elderly participants ranged from 72 to 93 years. Only two male caregivers participated in this study. The experiment lasted for 5 days, applying a repeated-measures design methodology [91], with an AB-BA format for counterbalancing. The sensor platform consisted of a waist-mounted smartphone, with in-built inertial sensors (accelerometer and gyroscope) to detect six activity states (walking, laying, standing, etc.). An abstraction layer was used to map activity states to activity levels (low and high) for privacy

Table 3.1 Summary of themes/findings in the preliminary experiment

Theme	General findings
Autonomy	One elderly participant emphasized the need for having a sense of independence and competence to execute his ADL and lead a normal life.
Social support	Generally, our elderly participants did not succumb to the loneliness ageism stereotype as they actively sought to maintain social connections with their families, friends, and neighbours.
Rituals	Three common rituals were observed during the interviews, which included improving physical well-being through sporting activities, church attendance for spiritual growth and community involvement to enable a richer and more enjoyable ageing process.
Guilty feelings	Due to busy lifestyles, a few caregivers reported that they felt guilty for not calling or visiting their elderly relatives and as such were more appreciative of technologies to increase awareness and augment social connectedness.
Tension reduction	One caregiver mentioned that the receipt of a close family member's context information could increase emotional anxiety especially if one knows that the individual is ill. Thus, he proposes decreased interactions as a coping strategy.
On-demand service	Some caregivers highlighted the relevance of being able to turn off ambient device as needed.
Privacy	Some participants were extremely concerned about the ethical and the privacy implications of receiving context information including the following: the type of information shared, access rights, and potential security risks.
Cynicism	A few elderly participants were sceptical regarding the use of assistive technologies for improving social connectedness. In reality, they were more appreciative of classical communication techniques such as telephone calls or face-to-face interactions.
Aesthetics	Warm colours were generally appreciated among all participants. Also, some participants demonstrated the need for customisable colours.
Value of the non-conscious processes	Some caregivers mentioned that certain colours could implicitly invoke pleasant memories, impart meaningful information and thereby positively affect moods and interpersonal relationships. Moreover, subtlety was highly valued by the participants concerning embedded sensors and inconspicuous light sources that could be easily integrated into the participants' environment.
Risks and emergencies	Even though our bidirectional application was directed towards social connectedness, risks and emergencies were recurring themes among most participants.
Accuracy and reliability	Caregivers generally highlighted the value of highly reliable and accurate information sources to avoid false positives within AAL environments.
Relevance to the frail elderly	There was a common tendency to assume that assistive technologies were more relevant to the weak and frail elderly among the elderly participants.

preservation purposes. Moreover, pre-attentive attributes such as colour, speed, and form discussed in [92] were used to communicate activity levels to participants.

Overall, the study results indicated that participants generally had positive experiences with the system [69]. Moreover, the findings showed that the subjective rating of relationship closeness was higher after system deployment. The most remarkable comment regarding the bidirectional display was the sense of co-presence it gave whereby a caregiver participant commented that she 'literally' felt her mother's energetic presence while at work. In addition, the majority of the participants remarked that they could see the value of the system to increase their awareness of their loved ones' activities as well as they generally appreciated the sense of privacy it gave. In essence, all the participants mentioned that the display provided a certain assurance that all was as expected with their loved ones. Also, some elderly participants saw a direct value in the tool for activating reflection on past interactions with loved ones. Furthermore, some elderly participants commented on the benefits of the system for stimulating mental activity, such that they likened the system to a puzzle, whereby they would actively try to determine what their loved one was doing. Table 3.2 summarizes the major findings in this experiment [69].

Table 3.2 Summary of major findings in the second experiment

Theme	General findings
Positive perception of the bidirectional peripheral awareness systems	Participants generally articulated that bidirectionality was equally necessary to strengthen social interactions between the elderly and their counterparts. This was reflected by an increase in telephone calls and face-to-face visits post system deployment.
Sense of security and peace of mind	Some caregivers argued that the system triggered an indirect sense of assurance knowing that their family members were healthy and active.
Accessibility and affordability	Two participants expressed satisfaction that context-aware solutions were now affordable and accessible as in the past it was merely accessible to incredibly wealthy people.
Positive perception of the abstraction of activity information	Participants generally appreciated the abstraction of activities as they felt it gave a sense of privacy and conveyed a measure of mysteriousness in trying to reason what the other person was doing. Thus, stimulating an engaging, lively, and fascinating interaction with their counterparts.
Promotes reflection	A few elderly participants mentioned that the system triggered memories of their past interactions with caregivers and helped them to recollect moments of high activity in their youthful days.
Reliability and accuracy	For health purposes, accuracy and reliability, were recurring themes throughout the post interviews.
Value of aesthetically pleasing designs	The aesthetic value of the patterns was highly appreciated by the participants, thus demonstrating the significance of colour, form, speed, and motion in the design of ambient displays.

3.8 Challenges

Although designing context-aware systems to support social connectedness between the elderly and their caregivers is a promising research venture, it is not without challenges.

As de Barros and Vasconcelos [93] argued, there are certain ethical principles that should be considered before conducting research with senior citizens. For instance, the researcher should bear in mind that activities with older people should last only for a short duration. In the case of this chapter, as discussed in [69], it was initially difficult to recruit some elderly participants as they thought the experiment was too extensive. This was countered in [30] by the use of creative and imaginative tools to unleash their curiosity, imaginations, and ideas about the possibility of the system. Another challenge points to the individual differences in the level of concentration and alertness of both target groups. In the case of the elderly, discussions with property managers, caregivers and elderly stakeholders revealed that experiments were best conducted with the elderly in the mornings. This can be attributed to reports and observations of high peaks of alertness and concentration of the elderly participants.

Also, even though permission was granted from the property manager of a Canadian independent living facility for the experiment discussed in [69], opportunities for caregiver recruitment proved difficult. In fact, some caregivers declined to participate due to time constraints and the geographical distances between themselves and their elderly loved ones. Thus, hampering the participation of many potential elderly participants.

Moreover, since the experiment was a real-life setting, privacy was critical. Concerning the collection of activity information, participants were assured in the informed consent that audio and camera sensors were disabled and they could discontinue the experiment at any point of the study [69]. However, two elderly participants reported that they did not discuss private matters while wearing the smartphone for fear of privacy violations. Arguably, this self-conscious awareness of the smartphone could be attributed to the short duration of the study. For that reason, a longer experiment is necessary to moderate such effects of self-awareness. On one occasion, one elderly participant reported that she did not know if the ambient display was capable of visually sensing her home activities. Nonetheless, she asserted that she proceeded with her activities as normal due to her trust in the principal researcher. This confirms the importance of gaining the elderly's trust when conducting research with ambient displays.

Finally, the short duration of study factored certain limitations, such as novelty effects [69]. In some cases, more attentional resources were utilized due to curiosity than anticipated. It is estimated that a long-term study could gradually stabilize the effects of novelty over time.

3.9 Conclusion

This chapter endorses a user-centred approach to designing context-aware systems for supporting social connectedness between the elderly and their caregivers. It demonstrates that by placing users at the centre of the design process, system usability, attractiveness, and acceptance can be enhanced. Moreover, the chapter emphasizes the importance of understanding the users' social context before deploying AAL innovations for social support.

To increase the acceptance of pervasive sensing technologies in AAL, careful consideration must be given to user comfort regarding the amount and location of deployed sensors. Consequently, we have explored the use of a single waist-mounted smartphone to take advantage of its multiple embedded sensors for collecting activity data and deploying as little wearable sensors as possible.

Furthermore, our findings suggest that participants are increasingly aware of the ethical and privacy implications of collecting and retaining their physiological data and as such demonstrated the need for assistive social technologies that preserve their privacy. Also, to reduce false messages in communicating the elderly's well-being information, the chapter advocates for accurate and reliable HAR models to precisely represent the users' context and gain their trust in the system.

In addition, in presenting contextual information, bidirectionality and abstraction are two critical features of social connectedness systems so as to engage the minds of the elderly and reduce privacy invasion concerns often expressed in unidirectional systems (where only the caregivers receive the elderly's contextual information).

Concerning the limitations, we acknowledge that a larger sample size would have contributed to our findings. Nevertheless, the current findings are in line with similar studies, for example, [50], deploying activity-based displays for social connectedness. Recruiting a larger sample size in subsequent studies may be challenging due to time constraints imposed by the experiment and the willingness of regular participants to deploy AAL solutions in their homes. However, collaborating with elderly care agencies could substantially circumvent the recruitment problem.

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Further reading

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Data set

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Biographies

Kadian Davis is a Ph.D. candidate in the Erasmus Mundus Doctorate Programme in Interactive and Cognitive Environments (ICE) at the Eindhoven University and the University of Genova. She serves as the Ph.D. representative for ICE students and is currently pursuing research in the area of design for social interaction for AAL environments, where she has made academic presentations in Portugal, the United States, China, Japan, Spain, and Italy. She pursued a bachelor and master of philosophy degree in computer science at the University of the West Indies (UWI), Jamaica. Prior to her Ph.D. scholarship, Davis worked as the head of the Information Technology Department at the University College of the Caribbean (UCC) for 2 years and as a teaching assistant for the Department of Computing at UWI for over 4 years. Her other research interest lies in the field of Internet Governance, where she serves as a member of the Internet Corporation for Assigned Names and Numbers (ICANN) and the DiploFoundation. She has also received fellowships from global organisations, such as ICANN, the Internet Society (ISOC), Verisign and the

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Evans B. Owusu is an independent researcher with research interest in machine learning, data mining and service oriented architectures. He currently works as a software engineer in the semi-conductor industry. He obtained his Master of Science in Embedded Systems from Eindhoven University of Technology and a Bachelor of Science in Electronic and Computer Engineering from the Polytechnic University of Turin. He was a research trainee at the European Commission Research Center in Ispra, Italy, between October 2011 and September 2012.

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