Persuasive Technology to Support Active and Healthy Ageing: an Exploration of Past, Present, and Future

Abstract

The age of the population worldwide is rapidly increasing, bringing social and economic challenges. Persuasive technology can alleviate the burden on traditional healthcare services when used to support healthy behaviors, for instance in the prevention and treatment of chronic diseases. Additionally, healthy behaviors are key factors for active and healthy ageing by delaying or even reversing functional decline. In this manuscript, we present a multi-perspective analysis of technologies that can be used in the support of active and healthy ageing in the daily life. First, we take the perspective of physical and mental health, by focusing on the promotion of physical activity and emotional wellbeing. From a temporal perspective, we look at how technology evolved from past, present and future. The overview of the literature is structured in four main sections: (1) measurement of current behavior (monitoring), (2) analysis of the data gathered to derive meaningful information (analyzing & reasoning), (3) support the individual in the adoption or maintenance of a behavior (coaching), and (4) tools or interfaces that provide the information to the individual to stimulate the desired behavior (applications). Finally, we provide recommendations for the design, development and implementation of future technological innovations to support Active and Healthy Ageing in daily life.

Keywords:

Monitoring; reasoning; coaching; older adults; emotional wellbeing; physical activity

1. Introduction

The promotion and support of healthy aging is no longer a challenge concerning only healthcare professionals. It is expected that, due to the inversion of the demographic pyramid, by 2020, one in four individuals in the Netherlands should work in healthcare to cover all needs – an unrealistic prospect. In 2002, the World Health Organization (WHO) highlighted the importance of a multidisciplinary effort by defining Active Ageing as “*the process of optimizing opportunities for health, participation and security to enhance quality of life as people age*” [1, p. 12]. Thirteen years later, the World Report on Ageing and Health introduces Healthy Ageing as “*the process of developing and maintaining the functional ability that enables wellbeing in older age*” [2, p. 28]. While the definition of Active Ageing targets policy makers, Healthy Ageing, as presented by the WHO, places the individual as an active participant in managing his own health, focusing on prevention and the importance of healthy lifestyles. Healthy ageing compiles a functional perspective on health, far beyond avoidance of disease, in which personal factors (intrinsic capacity and functional ability), lifestyle behaviors (e.g. physical activity and nutrition) and environmental factors (e.g. age-friendly infrastructures) play crucial roles.

In 2005, Buettner [3] identified global areas where, statistically, people live the longest – the so-called *Blue Zones*. When searching for the common elements that make these five regions unique, Buettner identified a set of lifestyle and environmental factors [4]. One of the elements was "moving freely", i.e. having an active lifestyle, with no need for running marathons or going to the gym. Various surveys suggest that this active lifestyle is not achieved by a large part of the population in the Western societies. Among the 28 EU member states, the older adults are less likely than any other age group to be engaged in regular physical activity and report the longest time spent sitting per day [5]. In the USA, among the 75+, one third of the men and two thirds of the women report not engaging in any regular physical activity [6]. When talking about physical activity promotion, people often think about exercise, or complete changes in their daily life, but that does not need to be the case. Leisure time physical activity, transportation, household chores and even game playing are mentioned in the guidelines for physical activity as an important way to get the recommended daily activity [7]. Furthermore, these activities support individuals in being engaged in community activities, another common factor associated to longevity in the identified Blue Zones, and a key determinant in several theories of Successful Ageing [8], [9]. Therefore, it can be hypothesized that one potential approach to support active and healthy ageing is by encouraging and motivating individuals to be engaged in activities that are pleasurable and contribute to daily physical activity, thereby contributing to both physical and mental wellbeing.

Changing behavior is difficult, but technology can assist through the application of several strategies, such as creating awareness about a current behavior or providing motivation to engage in healthier behaviors. Persuasive technology refers to technology designed to change attitudes or behaviors [10]–[12] and can thus be of great importance in supporting active and healthy ageing. Nowadays we are surrounded by technology aiming to influence our short- and long-term behaviors. When aiming at behavior change, it is important to fully understand which persuasion features lead to the success of the intervention. Therefore, we require we require systematic ways that can guide us in the design and evaluation of successful persuasive techniques. One example is the Persuasive System Design (PSD) model proposed by Oinas-Kukkonen, which offers a theoretical-conceptual framework that classifies persuasive techniques into four categories: primary task-, dialogue-, credibility- and social support

[12]. This model can be used not only as a guide in the design of new persuasive technology, but also serve as a tool to evaluate existing persuasive technology, for example, by identifying the persuasive features that are critical in the effectiveness of eHealth interventions [13], [14]. In this study, we provide a critical look at several examples of technology aimed at supporting active and healthy ageing guided by the persuasion system features identified in the PSD model.

Development of technology for older adults specifically has various pitfalls. The acceptance of technology to support healthy ageing has been extensively studied in literature (e.g. [15]–[20]), and it depends on personal (e.g. functional capabilities), technological (e.g. cost) and environmental factors [15], [17]. Previous experience with technology is suggested to increase technology acceptance and reduce fears [19], [20]. Especially when the initial technological skills are low, it becomes crucial to provide sufficient time and opportunity to the older adults to test the technology and to ask questions [15], [21]. Doyle and colleagues provide a set of recommendations regarding the design, development and evaluation of technologies with older adults [21]. However, most of this research is performed on technology to be implemented in the houses of the older adults, such as emergency support or fall detection. Such technology is not the focus of this article. Instead, we investigate technology that supports active and healthy ageing that can be of most benefit to those older adults who are not frail, supporting the prevention of functional decline and self-management of chronic disease.

With age come inherent biological changes that often lead to health impairments. However, there is no such thing as "the typical older adult". While some individuals reach considerable old age with minor physical or cognitive limitations, others experience a steep decline after an event (e.g. accident) or due to natural and progressive chronic diseases. There are, instead, several trajectories of age, defined not only by the impairment, but also by the ability of the individuals to cope with those impairments [2]. Furthermore, these impairments can be permanent or temporary; there is not only a large heterogeneity among individuals, but the status of individuals can also significantly change over time. Design and development of technology should not be geared towards the factor "age", but rather should focus on specific abilities or impairments, such as sensory impairments (e.g. visual and auditory) [22], lack of motivation, or ability to cope with changes.

Although a large body of literature on the topic of persuasive technology exists, developing successful tools to support a wide variety of older adult users in their everyday lives remains to be a challenge. In this manuscript, we take a critical look at past developments and current state-of-the-art of the technology components to support Active and Healthy Ageing in daily life, focusing on promotion of physical activity and emotional wellbeing.In order to structure our overview, we have divided the research area into four categories. Categorizing this from a technological perspective, and looking at tools or interventions that support an active lifestyle, we identified: (1) measurement of relevant parameters related to daily behavior and context (*monitoring*), (2) analysis of the data gathered to derive meaningful information (*analyzing and reasoning*), (3) defining, selecting and personalizing of coaching strategies to support adoption or maintenance of a behavior (*coaching*), and (4) tools or user interfaces that provide the information to the individual to stimulate the desired behavior (*applications*[1]). These four categories are not meant as an ontological division and, instead, serve the purpose of providing an organizational structure to the document. Sections 2 (monitoring), 3 (reasoning) and 4 (coaching) provide a historical and state-of-the-art overview of the topics, while in Section 5 (applications) we focus on providing a critical commentary to the examples given from the field of persuasive technologies to support active and healthy ageing. We base this commentary on the framework of the persuasive systems design model by Oinas-Kukonnen [12].

2. Monitoring

In many ways, "monitoring" is the first step in the chain of concepts involved in the development of technology for supporting healthy ageing. Monitoring concerns the collection of information from any source with or without direct involvement of the user himself. In this sense, monitoring can be performed with sensor devices placed on the body of the user (e.g. step counters) or in the environment (e.g. cameras), but it can also mean requesting direct information from the user (e.g. through questionnaires).

Monitoring in supporting healthy ageing includes two areas: monitoring of the *body* and monitoring of the *mind*. To provide support, we need to know about the individual's physical behavior (body), as well as his emotional wellbeing and his attitudes towards health in general (mind).

2.1 Physical Activity

The need for physical activity in daily life was already acknowledged in the early beginnings of the 19th century, for example thorough physical education among the youngsters [23], [24]. The empirical studies on physical activity during the first half of the twentieth century focused mostly on physical activity at work [25] and within the context of university or school sports programs [26]–[28]. The work of Jeremy Morris and colleagues is pioneering in relating physical activity to cardiovascular function and one of the drivers for the research on the benefits of physical activity on health in general. Morris, named by The Financial Times as *"the man who invented exercise"* [29], from his cohort study held between 1947-1972 with more than 30.000 male motor-drivers, noticed that those participants whose

[1] We will use the term *applications* from now on as a grouping term for any type of tools, interventions, mobile or web apps that *apply* the methodologies described in this work.

occupation required high physical activity had lower rates of coronary heart disease than their peers with more sedentary occupations [30]. Later, Morris and colleagues widened the scope of the work to the study of other occupations concluding that the incidence of coronary disease was higher in those with sedentary occupations in general [31]. The cohort study of Jeremy Morris and the Tecumseh community health study in 1965 [32] are among the first large epidemiological studies reported. The first half of the 20th century also introduces the notion that not all physical activity is the same and that one should clearly look at the different levels of intensity [25], [33]. When aiming at assessment of behaviors in daily life, the study from Jackson and Kelly is a pioneering in its investigation of the relation between self-reported physical activities in daily life and blood sugar levels among youngsters.

The second half of the 20th century saw an expansion of the research on the benefits of physical activity on health. Several meta-analysis studies have reviewed the work done during this period on the benefits of physical activity on physical and mental health of the aging population [34]. Most of this work is performed in large populations using self-reported questionnaires as the assessment strategy. Due to these efforts, there are currently more than 80 validated questionnaires for the assessment of physical activity [35]. Large populations can be reached easily with questionnaires allowing large epidemiological studies on physical activity [36]. However, assessment of physical activity is relevant not only for epidemiological studies, but also to evaluate effectiveness of interventions promoting physical activity. Such interventions require repeated assessments of physical activity over time to detect changes in patterns and to design individual plans for promotion of physical activity [37]. Questionnaires can fulfil this task but they lack objectivity and accuracy as they rely on the recall ability of the respondents [38], [39]. Van Poppel and colleagues investigated the measurement properties of 85 questionnaires and concluded that only one out of 41 studies presented sufficient construct validity when correlated to objective measurement of physical activity [40]. In fact, large differences were found between self-reported and objectively measured levels of physical activity among older adults [41] and adults in general [42]. Furthermore, their repetitive use can be bothersome to the individual, often leading to drop out. Therefore, more objective, and less obtrusive, ways of monitoring physical activity in daily life were needed.

The placement of sensors on the body to measure parameters related to physical activity over time goes back as far as the beginning of the 1980s, when Polar launched their first wireless wearable heart rate portable monitor focused on improvement of sports performance [43]. This was a niche product related to sports physiology, not a matter of public health. It was also in this decade that the first accelerometer-based physical activity monitor was adopted by researchers [44]. During these early years, accelerometer-based research appeared to be of interest of a certain niche of researchers and presented concerns related to the accuracy of the devices [45]. However, this situation rapidly changed. One of the first steps was to adopt a common definition of physical activity. The definition proposed by Caspersen and colleagues is still the preferred one and states that physical activity is *"any bodily movement produced by skeletal muscle that results in energy expenditure"* [46]. This definition does not limit the notion of physical activity to structured exercise, but instead considers any movement done in daily life. In terms of ambulant monitoring of energy expenditure, the doubly labeled water technique [47], [48] remains the Gold standard; however, this method is too expensive to be applied in large scale studies or in studies targeting daily life use [49]. Therefore, the recommended method might be to use an accelerometer that is validated using the doubly labeled water technique [50]. The interest on objective measurement of physical activity in daily life for several consecutive days seems to have appeared in the beginning of the 2000s [51]. A big improvement compared to early accelerometers was the ability to obtain real-time data [52]. It is in the beginning of the millennium that the terms 'wearables' and 'ubiquitous computing' appear connected to physical activity [53]. Since then, technology changed at an incredible rate bringing the most diverse opportunities and challenges to monitoring of physical activity with wearable devices.

Not only the technology was available, but there was also the recognition of a need from public health initiatives to promote physical activity among people of all ages. Physical inactivity is now identified as the fourth leading risk factor for global mortality and one of the modifiable risk factors for chronic diseases [7]. For the aging population, physical activity provides innumerous benefits, for example, for the prevention of functional decline and maintenance of independence [54], [55]. Furthermore, the inversion in the demographic pyramid and consequent increased costs associated to the management of chronic diseases, started a trend in healthcare to go from curative to preventive healthcare, as well as to make the individual responsible and pro-active in the management of his or her own health. This involves collection of data in daily life, to evaluate patterns and detect domains that require intervention.

The devices used in the laboratory setting for measurement of physical activity are often big, uncomfortable to use, expensive, and not appealing to long term use in daily life. The 2010s marked the advent of a new market of consumer available physical activity monitoring devices, often smaller, cheaper, more comfortable and therefore suitable for continuous use for long periods of time. Companies such as Fitbit, Jawbone, WiThings and Misfit promise a revolution in physical activity monitoring, mostly focused on the young, healthy consumer. Due to their various advantages, more and more research is being performed with these devices. They allow us to leave the lab and better evaluate activities during daily living but also come with drawbacks. The validity and reliability of these commercial sensors has been evaluated in systematic reviews, suggesting that consumer-based wearables provide high validity of steps in laboratory studies and variable correlation in daily life studies (cross correlation ranging from 0.36 to 0.86). However, validity and reliability of measures of energy expenditure was much lower [56]. Another concern relates to the fact that none of these devices allows direct handling of the data. This means that the data is not directly accessible to the researcher, but, instead, stored in servers often located in other continents. To overcome possible privacy concerns, data storage must comply to the regional (e.g. European) and country-specific guidelines. For example, in the Netherlands, data storage and processing must adhere to the Dutch Personal Data Protection Act [57]. This issue can be solved allowing open access to devices at a reasonable price, with the data being provided directly to researchers, complying with privacy guidelines. Another concern related to these devices is the fact that their algorithms are a black-box. For example, we do not know the algorithm to categorize bouts of physical activity according to their intensity (e.g. inactive, light activity, moderate activity and vigorous activity), bringing uncertainties for clinical assessment when looking at distribution of bouts of activity throughout the day or week. Finally, a risk when performing studies in daily life with wearable devices, is that we do not know if the person was actually using the sensor or not, although this issue could be solved by incorporating other sensors, such as those measuring skin temperature [58]. Finally, commercial devices often target a young, healthy population. This is understandably an effective marketing strategy but it does not mean that older adults are not willing to use physical activity trackers in daily life. On the contrary, older adults are curious about the technology. After using a wearable associated with a mobile application that collects and shows the data for a period of four weeks, most of the older adults in the study perceived an added value and reported that it helped them becoming more aware of their daily activity [59]. To overcome situations when stigmatization associated with age is an issue [20], [60], companies can consider discrete options, for example, wearable devices that can be worn in the pocket or under the clothes. Despite their flaws, commercial devices are worth considering for behavior change interventions due to their practicality and the fact that they are able to be used for longer periods of time [61], being suitable for the support of active and healthy ageing in daily life.

The future of monitoring devices looks promising. The continuous evolvement of technology brings innumerous possibilities to the field of physical activity monitoring, and devices are not limited to wrist bands or waist-worn devices. Technology provides diverse possibilities for wirelessly monitoring of physical activity both in the home as well as in the working environment [62]. The methods most often used to identify the location where physical activity is performed are global positioning system (GPS) sensors, wearable cameras and radio frequency identification [63]. The trackers as we currently know can also change completely. Smart textiles [64], pills, in-ear devices and smart tattoos, or even implantable sensors might revolutionize the way we monitor our health, including physical activity.

Almost everyone these days carries a super computer in their pocket. Although not really considered a wearable sensor, the mobile phone also provides the possibility to monitor physical activity in- and outdoors. The drawback is that, as it is not attached to the body, people might forget to carry it around all the time, namely in the home environment where they are more relaxed. Nevertheless, the computational power of the smartphones enables real-time activity recognition.

There are many different tools and techniques for monitoring physical activity, summarized in Table 1, each with their own complex interactions of advantages and drawbacks. The message is that when designing an application for supporting active and healthy ageing, it is important to be aware of these properties, and to be aware of the different individual preferences of the individual user.

Table 1 - Monitoring methods and tools for physical activity assessment.

Method	Monitoring tool
Self-reported	Questionnaires Experience Sampling
Wearable monitoring	Wristbands/Watch Smartphone Waist band Necklace/Ring Smart Textile
Global Contextual	GPS Smart cities: Internet-of-Things
Local Contextual / Indoor location	Radio Frequency Identification Integrated circuit tags Ultrasonic
Implantable monitoring	Chips

Throughout this manuscript, we consider persuasive technologies in the active and healthy ageing, focusing on daily activities that contribute to physical and emotional wellbeing. In this way, it is important to know the context in which the activity is taking place, as well as the feelings, mood and experiences induced in the individuals. One strategy to do so is through the experience sampling method, which will be discussed in the next section.

2.2 Emotional Wellbeing

Subjective wellbeing concerns the presence of positive affect, absence of negative affect, and a cognitive appraisal of satisfaction with life in general [65], [66]. Emotional wellbeing is identified as the emotional component of subjective wellbeing [67]. It concerns the experience of pleasurable engagement with the environment, eliciting feelings, such as happiness and serenity [65], [68], [69].

As positive emotions concern feelings experienced at a certain moment, they are prone to influences from the environment and context of the individual [68], [70].

Subjective, and more particular, emotional wellbeing has been studied for many decades [65], [71], [72]. In 1984, Diener reviewed measurements of subjective wellbeing, identifying 17 different assessment tools, including single- and multiple-item scales [66]. Subjective wellbeing is so important in multiple domains that in 2013 the Organisation for Economic Co-operation and Development (OECD) released the OECD Guidelines on Measuring Subjective Wellbeing [73]. While these guidelines intend to guide the surveys on large populations, they are not suitable for assessment of emotions and feeling associated to a specific activity or situation, as it is the aim of this overview of the literature.

Diary log methods are very commonly used. For example, in the Day Reconstruction Method [74] individuals are asked to start by sequencing the episodes of the previous day, report on the context of each episode (e.g. time, location and companion) and the respective emotions associated to each activity. Although initially applied within the field of Psychology, this method is now used in various fields, such as economy [75] and marketing [76]. Using the Day Reconstruction Method, White and Dolan looked at the pleasure and reward domain of daily activities among adults [77]. Outdoor activities were the most pleasurable, opposing to work activities. However, work activities were the most rewarding. On the other hand, relaxing and watching TV were placed in the positive axis of pleasure but experienced as being the least rewarding. Online versions of this method are to be found, such as in the Happiness Pointer [78] (in original: G*eluksWijzer*) which objective is to make the participants aware of what makes their happy or constrains their happiness.

The Experience Sampling Method (ESM), also known as Ecological Momentary Assessment, was introduced in 1987 and concerns the assessment of feelings or activities at the current moment that they happen [79]. ESM gained a lot of interest more recently, with the spread of smartphones and mobile technology in general. ESM provides several advantages over methods such as the Day Reconstruction Method. The most often mentioned is that it reduces the recall bias as individuals are asked what they are doing at the current moment [80], [81]. Secondly, it consists of short questions designed to avoid disturbing the individual, and allowing collection of data for long periods of time.

Despite its advantages, the use of experience sampling method to infer about human behavior has also several drawbacks. One of the concerns when fusing data from different sources is the veracity of the data collected. For example, one might be interested to know the energy expenditure (collected via accelerometer) while performing a certain activity (collected via experience sampling), as in [82]. The moment when the person answers the question is chosen by oneself and it is almost always interrupting the current activity of the person. This is particularly important when assessing feelings as the person can become annoyed only because of the interruption. The interruption of routine becomes even more relevant when using ESM to obtain information regarding the context of physical activities. It is unlikely that the individual will stop a jogging session or a tennis game to answer the questions on the smartphone. Probably, the person will finish the game and then answer the question. In this way, the answer “playing tennis” to the question “what are you doing now?” is strictly speaking no longer true. The person *was* playing tennis, now he/she is answering to a question on the phone. So, if we look at the physical activity of the person at the moment of the answer, or closely before it, it is unlikely to correspond to the physical activity of the person while performing the activity, in this case, playing tennis. A second concern is the obtrusiveness, and associated burden, of being engaged in a study with ESM [81]. A solution might be using context sensitive ESM whenever possible, and avoid situations when the person is in the middle of an activity, unless, when that activity is exactly the situation of research. Towards this end, in 2003 Intille introduced the concept of context-aware experience sampling (CAES) [83] and it had been further developed for several purposes. For example, Mehrota and colleagues have proposed a method that finds the opportune moments to ask questions based on prediction models, aligned to the lifestyle of the participant [84]. Another possible improvement to ESM would be a way to guarantee that the interruptions are short enough not to disturb the activity at all. To do so, smartwatches might be a good media as suggested by Intille [85]. Finally, one can think of automatic recognition of activities through analysis of accelerometer data combined with contextual information, such as location, to reduce obtrusiveness.

Another issue concerning ESM relates to the repetitiveness of the questions that may lead to familiarization. One of the advantages most often mentioned regarding ESM is the fact that it reduces memory recall bias. However, repeating always the same questions for a period of time might lead to familiarization as reported by [59], [86] suggesting that through repetitiveness, people can give impulsive answers because “they already know the question”. All-in-all, burdensome inquiries can lead participants to answer falsely, do not answer at all, or even drop out of the study [81], compromising the quality of the research.

One concern when deploying studies with ESM among older adults, is the fact that older adults are not familiar with the technology necessary (often smartphones). In our previous studies, we did not encounter any specific problems in this regards [59], [82], as long as appropriate training on the procedures and usage of the equipment was given to the participants, as well as a paper manual with all the information needed, as recommended by [21], [81].

Physical activity and emotional wellbeing are two different concepts to be measured, bringing specific challenges. First, one can think of the degree of subjectivity. Physical activity can be understood as a physiological measure that can be measured with sensors, i.e. translated to an objective measure (in this case acceleration). As an example: an acceleration of 1 m/s^2 means the same for all individuals in all parts of the globe. Contrarily, measures of wellbeing bring several challenges in its interpretation. In line with the criticism towards self-reported physical activity, self-reported measures of wellbeing are subject to personal interpretation. When asked on a scale from 1 (not at all) to 7 (totally) how happy people felt during the day for a period of one month, some people may report a score of 7 when they have experienced a reasonably nice day, while others may reserve such higher range scores for special occasions exclusively. Furthermore, experience and expression of emotions varies with age [87] and across cultures [88]. When performing studies with ESM is therefore important to account for individual differences on the response to questions about emotions.

Until now we have only looked at self-reported assessments of emotions; however, as we have seen with the assessment of physical activity, recent technology developments are leading in the direction of automatic recognition of emotions. Affective Computing refers to the automatic detection of emotions mostly based on visual and/or audio signal analysis [89], [90], and highlights the multidisciplinary work between Psychology and Computer Science. Emotion recognition can be achieved through analysis of facial expressions, audio (e.g. voice) or audiovisual techniques [91]. For the older population, automatic emotion recognition can be integrated as part of the home-care systems [92]. Additionally, data mining techniques on text analysis are also being used in the automatic detection of emotions [93], [94], for example, in the use of social media [95], [96]. Emotion detection through environmental monitoring is also possible. For example, the EQ-Radio claims to detect emotions as happiness, sadness or anger with 87% accuracy using reflections on the human body emitted by a wireless router to detect heartbeat and breath [97]. Emotion tracking is also emerging as a field in wearable technology [98]. These devices base their emotion recognition on physiological parameters, such as skin conductance, heat rate and skin temperature, with convincing accuracy when compared to instruments used in the lab [99].

While requiring interaction with the user, even if only for the act of placing a sensor on the body, monitoring can be considered a form of persuasive technology. The user is aware that her behavior is being measured and might adapt it accordingly, for example with fear of judgement by the research team. Within measurement of physical activity, for example, it is common practice to ignore the first three days of data collection to minimize this effect.

Our environments are getting smarter and smarter with smart homes connected to smart hospitals, smart roads, etc. We live in smart cities. By connecting everything (internet-of-things), knowledge from computer science can enter in place and actually make sense of the data. The more we know about the individual user, the better we can tailor interventions to reduce obtrusiveness and to gather information about context and emotional experience throughout the day. Ideally, monitoring may be totally unobtrusive to the user, but with the technology currently available, we are forced to make smart decisions about which tools to use for which applications. Combining various monitoring methods may improve the accuracy of available knowledge in a further processing step. This further *analysis* of sensed data followed by logical *reasoning,* in order to acquire meaningful, semantically rich information about the user and his environment will be discussed next.

3. Analysis and reasoning

To promote pleasurable activities in daily life, and subsequently increase physical and emotional wellbeing of the older population, we need to combine information from the individual and her context. Through monitoring we can collect real-time data in daily life. However, most of the times the data collected is meaningless in its raw, or unprocessed, form. *Analysis* concerns the fusion of data sensed by multiple sources to obtain meaningful information for the users, to detect short- and long-term patterns, as well as deviations from those patterns. Thorough *reasoning*, we can find meaningful relations between data from several types. By doing that, persuasive technology can provide coaching in (near) real-time, to meet the context of the user at that moment and to adapt to changes in, for example, the behavior of the user. The computational power of ordinary technology used in daily life allows real-time feedback and coaching. Also, the eminent field of Internet-of-Things supported by the upcoming 5G networks, give the means for communication between devices and continuous information about the user and his context. The challenge is to make sense of the data and model it in a meaningful way, so that the user is supported in achieving the desirable behavior change.

Data gathered in daily life is not obtained in a controlled setting; it is noisy and incomplete, and as such we can rarely control if the data we are collecting is exactly what we think it is. The advent of less obtrusive monitoring is allowing more and more studies to be performed in daily life. Conventional analytical methods have difficulties dealing with this type of data and there are several groups dealing with adaptations to that fact. The book *Intensive Longitudinal Methods: an Introduction to Diary and Experience Sampling Research* from Bolger & Laurenceau provides valuable information on intensive longitudinal studies, i.e. studies "*with enough repeated measurements to model a distinct change process for each individual*", and it focuses mainly on multilevel analysis of the data [100]. Multilevel modeling is appropriate for the analysis of hierarchically structured data in which there might be a lack of independence among observations [101]. Data collected in daily life meets this description, as it is often structured in at least two levels (e.g. observations nested within subjects) or multiple levels (e.g. observations nested in days, which are nested within weeks, and finally nested in subjects). The predictors associated to a level can be used to predict variation in another level. For example, multilevel analysis can be used to investigate the association between psychological functioning (a subject-level characteristic) with variability of affect (an observation-level variable) [102]. In multilevel regression analysis, when observations are nested within subjects, the variation of the slopes and the intercepts is then the variation between- and within-subjects, respectively. Such methods allow us to look for general effectiveness of an intervention, for example, but also to the differential effectiveness, i.e. "who benefits from the intervention?" [103]. Multilevel modeling brings the flexibility of having different sample sizes in each level. This means that there can be X observations for individual A and Y observations for individual B. This is particularly important in studies in daily life as it is unlikely that all subjects have the same number of observations, making the analysis unsuitable for repeated measures analysis of variance (ANOVA).

To give some examples, in the field of physical activity, multi-level analysis has been used to analyze associations between predictors (e.g. demographic and environmental factors) with the time spent in moderate and vigorous physical activity intensity separately on weekdays and on weekends [104]. Using multi-level analysis, Corder and colleagues showed that, among a sample of 2,064 children, those with more parental logistic support were less likely to decrease their physical activity on the weekends during a one-year study, while peer support was more important during the weekdays. Multilevel analysis has also been used to investigate the relationships between affect and physical activity. For example, in a study with 62 university students aged between 19 and 30 years old, increase in physical activity was associated with positive and energetic feelings [105]. In this case, women felt significantly better (positive valence) after increasing their activity levels, when compared to man.

Despite the flexibility given by multilevel modeling, it still presents some challenges regarding, for example, categorical predictors. This type of variables can always be dichotomized (i.e. transformed into binary variables), leaving one out as reference, but this is not desired when a variable can assume a large number of values, and eventually leads to loss of granularity in the dataset [82]. Furthermore, while multilevel modeling provides several advantages for ad-hoc analysis, such as investigation of the effectiveness of interventions using persuasive technology, this is method is not suitable for implementing in real-time. These analytical methods, although not suitable to be used in real-time, give us the tools to understand behavior and create profiles.

A new trend in persuasive technologies is to bring techniques from the field of machine learning to conventional statistical tools. One example is the analysis and interpretation of human behavior as a neural network. In this network, each symptom (or variable of interest) is represented by a node. The weights of the connections between nodes and the changes to these weights over time, provide an indication of the relations and dynamics of the system. Bringmann and colleagues analyze personal neural networks with multilevel vector regression (VAR) models to investigate clinical longitudinal data [106]. The authors used this method to show that worrying plays a more central position on the network for people who score high on neuroticism than on people who score low. This personalized network analysis is being used in the field of psychopathology [107], for example in the prediction of depression. In this analysis, the dynamics of a personal network can be analyzed to detect proximity from a tipping point, by increased chaos and connections in the person's network [108].

A similar approach can be taken to analyze the dynamics of healthy lifestyles. For example, in a study to monitor and understand craving behavior, researchers investigated the contexts of healthy and unhealthy eating, in which a mobile application is used to ask participants about their activities, location, companion and emotional status approximately eight times a day. Furthermore, participants were asked to report everything they ate as well as craving for healthy and unhealthy food. The behavior of obese and non-obese participants was then modeled with personalized networks to investigate which factors are influencing the craving behavior for each one of the sample populations separately [109]. First of all, the network of the obese sample showed a much denser structure (i.e. more significant connections between nodes) than the network of the healthy-weight sample. Looking at specific nodes, negative emotions, such as sadness and boredom, predicted unhealthy eating on the obese sample and healthy eating on the healthy-weighted people. Additionally, this method allows individual analysis of behavior giving the opportunity to look at the network of each specific individual and, therefore, implement personalized interventions. Finally, by treating the networks as graphs, this method provides the possibility to analyze the centrality of the networks (i.e. outdegree, indegree and betweeness values), seeing which nodes play the more important roles in the networks and, therefore, deserve more attention.

To the best of our knowledge, the personal network analysis has not been investigated in the domain of healthy ageing. It would be interesting to look at the dynamics of healthy behaviors especially in the older population, modeling physical and mental health and to identify relations between different factors. This approach could for example be used to understand within-person differences in the influence of contexts in the promotion of physical activity. In the context of persuasive technologies, personal network analysis is a promising technique to investigate not only the effectiveness of interventions but also the contextual factors influencing the changes in adherence and adoption to technology over time.

To generate meaningful information to the users, behavior change systems can incorporate expert-knowledge, i.e. pre-defined knowledge from the user (e.g. age, gender, health status), user-knowledge (e.g. preferences) and data-driven features (e.g. from the data collected over a month it is seen that the user moves more on Saturday's than in any other day of the week). For example, Sprint and colleagues combine knowledge-based and data-driven features to perform unsupervised detection of changes in physical activity over time [110]. The analysis of long term patterns is a challenge that emerged with the amount of data that is possible to collect nowadays with wearable devices, environmental monitoring and personal devices, such as the smartphone. The coming years will likely bring exciting developments in this field, with large amount of information from the individual and his environment being collected by different sources, and new and more effective algorithms, supported by smaller and unobtrusive devices with large computational power.

While conventional statistical analysis gives us the possibility to analyze which intervention works for whom, (near) real-time data mining allows us to adapt the interventions to the current status of the user and his context. In this way, when a new user starts the intervention, he can be given the intervention that has shown most effective results on people alike, and the intervention can be further tailored in real-time. Adaptation is in fact a key of persuasive technology [12]. And adaptation over time is particularly relevant when the user is an older adult as the needs of this population are more likely to change than in their counterparts. Similarly, to the field of monitoring, also in what concerns analysis and reasoning techniques, we need higher transparency and communication between researchers and companies to meet the ultimate goal of promoting health and wellbeing.

Initiatives such as the Open Science Framework [111] are likely to help in spreading knowledge and implementations of algorithms in a transparent manner. Looking at initiatives such as Google's DeepMind [112] and IBM's Watson [113], artificial intelligence within the computer science field is bringing new horizons to behavior change support systems. Although smart reasoning can bring a wealth of meaningful information regarding the user, his context, and his behaviors, the next crucial step is to turn this information into meaningful actions to promote behavior change: *coaching*.

4. Coaching

Persuading someone to change a behavior is not easy. Psychologists have investigated the reasons and moderators that lead humans to break established patterns of action since long ago. Work from as far back as the beginning of the 1930s showed that, within the sports of Northeastern University in USA, improvement in physical fitness was more dependent on the instructor/coach than on the sport itself [27]. These results suggest that an external agent, in this case a human coach, can play a crucial role in the motivation of the individual to reach a desired behavior change. Furthermore, individual characteristics and the environment can be motivators or inhibitors of adopting new behaviors. In terms of support of healthy ageing, we encounter the challenge of persuading an older adult user to break a lifestyle pattern that may have been established over the course of many years or even decades. It is therefore of utmost importance to look at theories of persuasive technology and behavior change, and identify how these theories can be implemented in technology to improve the effectiveness of interventions.

The Social Cognitive Theory remains one of the most generally used theories in the promotion of healthy behaviors. Self-efficacy, one of its constructs, is defined as the belief in one's capability to organize and execute the courses of action required to produce given attainments [114]. If the individual has low self-efficacy, i.e. if s/he does not perceive himself as capable of adopting the new behavior, it is unlikely that the individual will be motivated to change current behavior. Therefore, technology interventions promoting healthy behaviors must ensure the user that he/she has the personal resources necessary to act in the desired manner. To do so, it is important to set not only a long term goal, but also short-term goals that are challenging but achievable, in accordance to the Goal Setting Theory [115]. In fact, setting appropriate goals is a key determinant of the success of any persuasive technology. Several reviews have shown the importance of goal-setting in behavior change interventions promoting, e.g. healthy eating [116], physical activity [117], and supporting self-management of chronic conditions, such as diabetes [118]. Looking at physical activity promotion, personalized goals are particularly relevant in the older population due to the heterogeneity of this group, as it is likely that older adults experience some degree of disability [59], [119]. Therefore, a daily physical activity goal should be set according to the current behavior of the individual, for example, by automatically setting daily physical activity goals adjusted to the routine of the individual [120]. In this self-adaptive goal setting, the system analyses the routine of the user, and set incremental challenging but achievable daily goals, that require small steps to reach the ultimate desired goal. The ultimate goal, as well as how the user should ideally distribute his/her activity over the day, can be set by a healthcare professional or based on the guideline that matches the user profile.

The Transtheoretical Model coined by Prochaska and DiClemente in 1983, suggests that a behavioral change process, whether it means recovering from problematic/addictive behaviors or adopting a new healthy behavior, involves movement through a series of five discrete stages: pre-contemplation, contemplation, preparation, action and maintenance [121]. Each one of these discrete stages is called a *stage-of-change*. In the early stages of this model – pre-contemplation and contemplation – the main strategies consist of creating awareness about the current behavior (without being aware, there is no perception of any need to change) and educate about the advantages of the desired behavior. When moving through the several stages, an individual should re-evaluate the goals continuously to keep appropriate goals that are specific, challenging and achievable that continuously adapt to the current behavior of the individual [115]. Setting goals that are too difficult for the user to achieve can lead to frustration and drop-out. Commitment to take actions is also very important, as considered in the strategy of implementation intentions, which states that an individual is more likely to take an action if he/she has previously committed to perform that action [122].

It is also necessary to take into consideration the reasons why an individual takes an action. The Self-Determination Theory defines two types of motivation: extrinsic and intrinsic motivation. While extrinsic motivation refers to "*the performance of an activity in order to attain some separable outcome*" (think of monetary reward), the intrinsic motivation "*refers to doing an activity for the inherent satisfaction of the activity itself*" [123, p. 71]. Experiencing pleasure or enjoyment while performing an action, is a motivator to repeat that action. Translating this to behavior change promotion, by learning what the user enjoys doing and adapting the coaching strategy accordingly, we are likely to increase the adherence to the interventions as the individual is more likely to comply with the advice. This strategy is a core component of the approach of promoting pleasurable activities in daily life to achieve Active and Healthy Ageing. The Self-Determination Theory is not the only theory referring to the driven effect of positive emotions in the promotion of healthy behaviors. Building upon the Broaden-and-Build Theory, which states that positive emotions broaden individuals' momentary thought-action responses and support in building a variety of resilience resources [68], Frederickson has introduced the 'upward spiral theory of lifestyle changes' [124]. According to this offshoot of the Broaden-and-Build Theory, individuals experiencing positive emotions are more likely to be open to new activities, and consequently initialize, new behaviors; these new activities, and behaviors support building of personal resources which enhance health and feelings of fulfilment and accomplishment for adopting the healthy behaviors, producing experiences of positive emotions, and creating an upward spiral. Furthermore, incorporating Berridge's perspectives on a difference between 'liking' (i.e. the same concept of pleasure as used in the Self-Determination Theory) and 'wanting' (similar to a drug addict that 'wants' to take a drug even when he does not experience pleasure with that action anymore) [125], [126], Frederickson suggests that there is an inner layer of the spiral, in which positive emotions, including those that go beyond pleasure, can be non-conscious motivators for sustainable decisions to maintain healthy lifestyles. The results of a systematic review on the relation between positive emotions and independence in performing activities of daily living match this bi-directional relation with longitudinal studies suggesting that those with higher levels of positive emotions at baseline are more likely to have better functioning at follow-up [127]. An hypothesis is given by Cooper and colleagues, who suggest that when older adults are faced with a decline in functioning, those with higher levels of positive characteristics are likely better at building a variety of personal, social and environmental resources to counteract that decline and keep their independence [128]. Building resilience resources is particularly relevant in the older populations, as with age, people are more likely to encounter adversity on the health domain (e.g. functional decline) and in terms of life-changing events (e.g. death of relative).

Unobtrusive technology facilitates learning what individuals do and experience in daily life, and apply the behavior change theories mentioned above. In fact, a meta-analysis from Fanning and colleagues shows that indeed technology-based interventions targeting promotion of physical activity are more effective when relying on behavior models [129]. Oinas-Kukkonen defined behavior change systems as "*information systems designed to form, alter or reinforce attitudes, behaviors or an act of complying without using deception, coercion or inducements*" [130]. Technology-based interventions to promote Healthy and Active Ageing fall into this definition. New behavioral models are also being designed having technology-based interventions in mind. One example, is Fogg's Behavior Model which suggests that new behaviors result from a combination of motivation, ability and triggers [131]. This means that an individual must be motivated and have the skills (ability) to perform a new behavior. The trigger given by the behavior change system must meet the motivation and ability of the individual at any given moment. Fogg defines three types of triggers: spark (when a person lacks motivation), facilitator (when a person is motivated but lacks ability) and signal (as a simple reminder when a person is highly motivated and has high ability). Even those who are intrinsically motivated to adopt a certain behavior, experience ups and downs in their motivation. Triggers in the path of the individual remind and highlight why the change in behavior is desired and, for example, why this is a good moment to take an action. This work resulted in Fogg's "Behavior Grid" which specifies 15 types of behavior, in a 3x5 matrix, where the first dimension concerns the duration of the intended behaviors (one time event, specific duration event, or permanent change) and the other dimension concerns, what the authors call, "Flavour" (new vs. familiar behavior, encourage vs. discourage vs. stop behavior) [132].

Each individual is unique, and dynamic, in a sense that a strategy that works for one, might not work for another, and even what previously motivated an individual in the beginning of the intervention might not motivate the same individual at a later point in time. Persuasive technology can benefit from what is nowadays called *personalized health*: each person has an individually 'tailored' plan, like a tailor fitting a suit. This means that we can tailor the interventions and the communication to the user. Since each individual is different, it is widely believed that tailoring, or personalization, helps increasing the adherence, and effectiveness, of technology promoting behavior change [133]. Hawkins et al. defined tailoring as "*any of a number of methods for creating communications individualized for their receivers, with the expectation that this individualization will lead to larger intended effects of these communications*" [134]. Ecological momentary interventions (EMI) is a general term given to interventions deployed in daily life with tailored communication to the individual [135].

A framework to provide tailored communication to individuals is given in [136], and identifies four properties that can be tailored to each particular instance of communication: timing (*when is the communication provided?*), intention (*what is the goal of the communication?*), content (*what is stated in the communication?*) and representation (*how is the communication presented to the user?*). In the following paragraphs we provide a set of examples in how to tailor, or personalize, each one of the properties of communication identified in Figure 1, that can be of use in persuasive technologies.

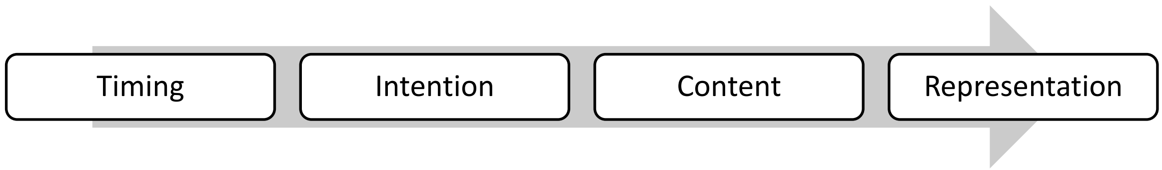

Figure 1 - Concepts for personalization of motivational messages. Adapted from [136].

Timing property corresponds to *when* the communication is delivered. The communication can be user-initiated, i.e. the user intentionally requests information from the system. For example, we can think of the user intentionally seeing how far he is from reaching the physical activity goal or requesting information about activities in his/her surroundings. Secondly, the communication can be system-initiated. In this case, the system decides when the communication with the user should be initiated. Tailoring the timing to individual users can occur through five distinct concepts: goal-setting (e.g. encouraging as a user is approaching his goal), adaptation (e.g. adjusting the frequency of nudging based on the user's stage of change), context-awareness (e.g. timing a message based on the user's location), self-learning (e.g. learning which moments are effective for reminders) and user-targeting (e.g. using a personal calendar to decide which moments better not to disturb). Without the proper strategy the timing of communication can be very wrong, as for example a system should not initiate interaction with the user when he/she is participating in a religious event, except if in an emergency situation.

Intention corresponds to the aim of the communication and it is always associated to a goal. Intentions might contemplate the motivation to increase certain behaviors (e.g. social activity and physical activity), decrease/cessation of a behavior (e.g. smoking and unhealthy cravings) or neutral (e.g. reinforcing the user that he/she is doing fine). Noteworthy is that, even when it comes to promotion of a certain behavior, as in physical activity, there might be moments when the system must discourage the user to engage in that behavior. For example, the system might discourage the user to do intense strength training two days in a row. When the intention of the communication is established, we can move to the content.

Content corresponds to the actual information that is given in a communication. The content of the message can consist of feedback (i.e. information about the status of the user), argument (i.e. a reason why the user should perform a behavior or action), and a follow-up which, in turn, can be a suggestion of an activity or a reinforcement. Suggestion of activities or behavior can be based on the lifestyle of the individual or on the context of the individual at a certain moment. For example, looking at suggesting activities to increase physical activity, Choi and colleagues propose a list with sports and activities to be performed at home with the equivalent number of steps [137]. The Metabolic Equivalent of Task (MET) can also serve as indication of the physical activity associated to different daily activities [138]. The promotion of physical activity can then be performed via proxy, i.e. motivating people to engage in activities of contexts which are likely to induce physical activity, but are not related to exercising, as suggested in [139].

Representation, the last property of a communication, is the way the message is represented to the user. This can be visual, e.g. through images or natural language, audio or haptic. The representation of a communication can be personalized, for example, to the context of the user. For example, when the user is at home he might receive audio messages in the sound system, saying that there will be a 15 minutes' window of sun in this stormy day, while when the user is at work, the same message should be given as a text on a device to decrease obtrusiveness. When targeting the older population, the choice of the representation should take into consideration possible visual and/or auditory impairments of the individual [22]. Several feedback and coaching modalities will be discussed in the next sub-section.

In this section, we have seen that behavior change systems must build on theories from Psychology to support each individual user in reaching the desired objectives. The field of Computer Science provides the tools to personalize an intervention to each specific user and to adapt to changes of the individual or the environment over time. Furthermore, data mining techniques can help identifying the most suitable intervention for a user based on his profile based on previous work to avoid the cold-start problem (i.e. lack of detailed information of a user in the beginning of an intervention). A promising initiative is The Human Behavior Change Project [140] which aims to synthesize evidence about behavior change, by systematically organizing and analyzing previous research and generate new insights about behavior change.

In the previous sections we addressed the gathering of relevant user and context data, processing of this data into meaningful information and the application of the right coaching strategies to turn this data into behavior change support. In the next section we look at the various tools that incorporate all of the previous parts in order to come to a tangible feedback and coaching tool.

5. Applications

Monitoring technologies, reasoning algorithms and coaching strategies are vital building blocks of persuasive technologies but must in the end be embedded in valuable tools and applications that support the individual in their Active and Healthy Ageing. We refer to *Applications*, as the interfaces that allow the system to communicate to the user. Recent decades have experienced a growth in the technological tools available to support behavior change. However, most of the technology-based tools for older adults focus on monitoring and detection of behavior (e.g. recognition of activities of daily living and fall detection), and are not persuasive systems for prevention and promotion of health and wellbeing. Nevertheless, there is an overall growing interest in the development of applications focused on prevention, as can be seen for example by the European Commission's efforts by setting up more than twenty-five million euros for the development of innovative projects on "Personalized coaching for wellbeing and care of people as they age" [141]. In this section, we will provide a critical look based on the persuasive systems design model at well-established and emerging persuasive technologies to support Active and Healthy Ageing, summarized in Table 2. With the increased adoption of mobile phones, several interventions made use of SMS messaging to promote behavior change, such as smoking cessation [142] or encouraging physical activity (e.g. [143]–[146]). When targeting the older population, SMS messages are often used as alerts to the caregivers (e.g. [147], [148]). Smartphones enabled a new way of intervention delivery. They allow real-time computation of data, and delivery of information or prompts to the user in engaging interfaces, for example in the promotion of healthy eating [149] or physical and cognitive activity [150]. Some of these systems, made it to consumer products, such as the Gociety tool, a solution consisting on a smartphone application, activity tracker and a mobile application for caregivers that supports the individual in maintaining independence and achieving an active lifestyle [151]. Supported by the current high adoption rates of smartphones, the number of mobile applications targeting promotion of health-related behaviors, including those targeting an aging population, is increasing rapidly. Due to their pervasiveness in the individual's lives, smartphones are a preferred medium for *dialogue support*, one of the key categories of persuasive systems according to the PSD model [12]. Smartphones are specifically suitable for episodic and short-term interactions, such as reminders and rewards. Another advantage of mobile applications is the fact that they are easily distributed, allowing developers to easily reach large populations of users, becoming important means for promoting *social support*. However, the human-machine interaction when using smartphones is often too shallow to provide a quality level of coaching. The phone, as a medium, is not suitable for an in-depth conversation between user and machine, which can be better achieved by other types of media, as will follow.

Another ubiquitous screen-based tool to deliver interventions is the personal computer. Although not suitable for real-time feedback, compared to the smartphone, the computer allows for richer dialogues between the user and the application, enhancing the *dialogue support* of the persuasive system. An example of a web-based platform to promote Active and Healthy Ageing was developed in the European FP7 project PERSSILAA [152]. In PERSSILAA, a novel service model was developed, implemented and evaluated to screen for and prevent frailty among community-dwelling older adults. Older adults were given tools to screen, monitor and train their health, in a multi-domain approach focused on the domains of nutrition, cognitive and physical functioning. After being implemented and evaluated in Italy and the Netherlands, one of the key lessons of the PERSSILAA service model was the importance of the motivation by leveraging *social support* [153]. To this end, PERSSILAA enabled social support achieved through human-machine and human-human interaction. Web-portals, such as PERSSILAA, have the disadvantage that they require the user to explicitly choose to initiate the interaction with them. In this regard, such applications are constantly fighting for attention with all the other tools and platforms that people might use their computer for. On the positive side, web-portals are easy accessible, often non-device dependent, and just like for mobile applications, can be easily distributed around the world, making them still one of the preferred media for delivery of eHealth interventions.

The area of Smart-Homes is another technology that is increasingly being used to support Active and Healthy Ageing through persuasive technologies. Smart-homes provide the means to combine several persuasive technology applications into one single service platform, with the aim to improve adherence and effectiveness of the interventions. While smartphones and other mobile systems allow for shallow monitoring wherever the user goes, smart-homes support user's primary task by allowing detailed *self-monitoring* of the user and being ideally suitable for *tailoring* by adapting the content to the needs of the user and possibilities of his own home environment. Furthermore, when in the comfort and privacy of the home environment, the user is likely to feel more comfortable to engage in deeper dialogues with the system, enriching the *dialogue support* that can be given. The European Funded FP7 project eWALL [154] is an example of a smart home environment designed and developed having in mind the needs of older adults with chronic diseases or suffering from age-related impairments [155]. The eWALL system supported users' primary task by *self-monitoring* physical and cognitive health of the user, combining wearables and environmental monitoring to infer the health status of the user at any moment, and supporting the user in achieving a healthy lifestyle by providing feedback and coaching on a large touch screen. Having physical, cognitive and social interventions into one single platform allowed for a holistic approach to self-management. For example, a COPD patient gets physical activity training combined with sleep. The drawback is that one tool with many different functions is created, which can escalate the complexity of the user interaction. In these cases, particular attention should be given to the user interface design in order to keep the platform interesting and useful. To increase the engagement of the user with the application, a virtual agent, a friendly robot called Robin, builds on the personalized communication framework described in the previous section to enhance *dialogue support* helping the users reaching the desired behaviors.

Virtual agents, or more specifically embodied conversational agents, can be considered the strongest interaction representation for *dialogue support*. By allowing richer dialogues between user and machine, virtual agents can leverage the principle of *similarity* in both looks of the agent and language used. For example, medical related information can be given using technical language by a serious-looking agent wearing a lab-coat while physical promotion can be given by an agent in a track suit with more informal language. The use of embodied conversational agents in the support of Active and Healthy Ageing has been explored in diverse areas, such as the agenda management for older users [156] or coaching in real-time to the performance of physical exercises [157], for both users with high, but also lower levels of health literacy [158]. These personal assistants, can be all-knowing, supporting the users in all components of their lives. Systems as Amazon's Alexa [159], Apple's Siri [160], and Google Now [161] are promising tools that may be used to support active lifestyles, also among older adults. Personal assistants can be embodied, either through the use of virtual agents displayed through an interface or on the upcoming field of holograms. For example, the Japanese company Vinclu Inc. recently announced the launch of Azuma Hikari [162], a female embodied hologram that assists individuals in their daily lives. In its released version, Vinclu Inc. targets a young and technology savvy audience, but it is easy to imagine the potential application to older populations. The difference here is that Azuma Hikari has a personality and preferences (for example, she likes doughnuts and hates insects) and supports her 'master' in all tasks of daily life, such as reminding of meetings or switching on the heating before the user arrives home. Virtual agents can be presented on a screen, hologram or in any other interface, such as a robot. For instance, robots can serve as the embodiment of physical training tools (e.g. [163], [164]). Robots allow for similar *dialogue support* features as embodied conversational agents, although their looks are limited by the physical characteristics of the robot. In geriatric care, these assistants might also fight loneliness, a very problematic condition of the ageing population. An example is the seal-like PARO therapeutic robot resembling a pet that needs to be taken care of, used in clinical (e.g. [165]) and non-clinical populations [166]. Also, there is a great interest in robots to be companions, or even to perform the role of butler. Daily interaction with robots can be performed to support activities of daily living [167] or improve mental wellbeing (e.g. [168]). This drive does not come only anymore from the healthcare demands, but also from the consumer perspective, as the case of the Zenbo [169] robot, presented in October 2016 by Asus.

Whenever a virtual coach is in place, it is perhaps most important to talk about credibility and empathy. Virtual coaches, as embodied agents or robots, provide strong opportunities to enhance *system credibility*, particularly emphasizing *trustworthiness*, *expertise* and *authority*. For example, in the future, we can think of a holographic representation of the physiotherapist to provide rehabilitation training in the home environment. Whatever the media of the agent, it is important that they show empathy, bringing the principle of *liking* from the PSD model beyond visual attractiveness. In this regards, Beun and colleagues reported that participants in their study on virtual coaching for support of insomnia therapy missed their virtual coaches after the end of the study, even knowing that "it's just algorithms" [170]. Designers can learn from the video-game industry or cartoons (e.g. Pixar Studios that have a long track record of bringing to life empathic virtual characters) how to design empathetic systems. Finally, in our opinion, it is crucial that virtual agents remain as supporters, and not replacers of human contact, especially in the case of the older population in which loneliness presents a serious concern [171]. Virtual agents, whether on screen, hologram or as a robot have the potential of providing the most natural form of interaction through natural language, facial and body language, and presence. As a downside, this form of interaction is not suitable for presenting all types of information. For example, patterns of behavior over time are more easily visualized in traditional graphical user interfaces, such as reminders and graphs.

Staying within the home environment, we can think of how objects of everyday life can be used in the support of Active and Healthy Ageing. One example already in place is to transform the typical photo frames available in every house to be smart displays to promote healthy behaviors (e.g. [172], [173]). An art installation in the house whose change in the leaves in the trees is a metaphor for the user's physical activity; a statue which position reflects the wellbeing of the person; promotion of behavior related to the function of the object, as in for example, the fridge supporting in healthy eating; there are many creative opportunities of bringing supportive technology into the lives of people that are not fully explored and exploited. By being physical objects in the environment of the user, the inherent presence of these tangible devices and robots is in itself a reminder of a certain behavior.

The final technological tool we want to talk about is virtual reality. Compared to other web-based technologies, immersive virtual reality provides the sense of presence, being able to recreate virtually any real or abstract environment imaginable. Virtual reality is a promising tool to face frailty challenges, for example in the early identification of frailty symptoms through the assessment of executive functions in a simulated environment of daily life situations [174]. Virtual reality facilitates cognitive [175] as well as physical training [176] in engaging environments, supporting older adults staying active for as long as possible. In our opinion, virtual reality will bring new paradigms to improve mental wellbeing by providing new means of entertainment and connectedness, especially for those living in remote areas. To reduce the burden of loneliness, one can think about the appeal of sharing experiences with virtual reality, in which the receiver can perceive himself as part of the event, such as a birthday or checking the new family car. Similar to what happens to robots and tangible devices, it is not desired to analyze virtual reality applications in line with the PSD model, as this model seems to be more suitable for mHealth and eHealth applications. One can say that the biggest advantage of the virtual reality is providing the possibility to simulate real-life situations, providing a real-word feel. However, this concept is not featured in the PSD model, in which the principle of *real-world feel* concerns “a system that highlights people or organization behind its content or services” [12, p. 494].

Table 2 – Summary of advantages, limitations and examples of persuasive technology elements of each type of application for interventions targeting support of Active and Healthy Ageing.

Type of Application	**Advantages for AHA[1] interventions**	**Limitations for AHA interventions**	**Example of persuasive technology elements (in line with PSD model[2])**
(Smart)phone-based	- Smartphone uptake increasing among older adults - mobile technology, always with the individual - multi-function (not dedicated device)	- limited possibilities for human-machine interaction	- dialogue support - social support
Web-based	- rich dialogues between user and application - easily accessible - easily distributed worldwide	- requires explicit initiative from the user to start interaction	- dialogue support - social support
Smart-homes	- combination of several technologies into one single platform - potential to total unobtrusiveness	- possible escalation of complexity when obtrusive, especially for those with cognitive impairments	- tailoring - self-monitoring - dialogue support
Virtual conversational agents	- empathetic systems - natural form of interaction	- not suitable to provide all forms of information	- dialogue support - similarity - trustworthiness

	overcoming accessibility constraints of older population (e.g. visual impairments, low literacy)	- interaction with "virtual humans" not always intuitive for older adults	- expertise - authority - liking
Tangible everyday life objects	- inherent presence in the environment works as a reminder of a certain behaviour - familiarity with everyday objects reduces barrier to use technology	- limited interaction possibilities	*Analysis not suitable*
Immersive virtual reality	- endless simulation of real-life situations - at this moment still a technology of the tech savvy population	- fear of closeness to the real-world	*Analysis not suitable*

[1]*AHA – Active and Healthy Ageing*
[2]*PSD – Persuasive Systems Design*

Regardless of the specific feedback and coaching application, those involved in the development and implementation of persuasive technology to support Active Ageing must think that the application is in support of the user, and with his best interests in mind. Furthermore, technology must be evaluated in several phases, with evaluation levels corresponding to the maturity of the technology, as presented in [177]. Virtual Reality, Robotics, and even Virtual Agents presented on more commonplace displays are all emerging fields that radically change the interaction between user and application. Although early adopters may completely embrace these upcoming and futuristic technologies, the true potential value in the field of Active and Healthy Ageing comes from designing applications that combine unobtrusive monitoring, smart reasoning, adopting personalized coaching strategies and combining it all in friendly and natural user interaction concepts that provide pleasant added-value to the life of the older adults.

6. Conclusion

In this article, we looked at the past, present and emerging solutions of the four components of technology to support active and healthy ageing – monitoring, analysis and reasoning, coaching and applications – that are needed to bring the experience to the users. The advances in technology in the last decades have resulted in smaller and less obtrusive monitoring devices that are suitable for use in daily life, efficient algorithms able to deal with complex and large datasets, personal coaches that follow us everywhere all the time, as well as new exciting means of interaction. We have looked at monitoring from the perspective of measuring daily physical activity behavior as well as of measuring emotional wellbeing and discussed the various methods available together with their advantages and drawbacks.

In terms of physical activity, although accurate and affordable monitoring devices are ubiquitously available, these are not necessarily designed with an older adult population in mind. When aiming to obtain information about the user's emotional state, one must consider whether the user is willing to be confronted with his/her emotional state. By asking directly, users are forced to think about and put their emotions on the table. In this case, less obtrusive methods, such as facial recognition or automatic analysis of the user's expressions on social media may be preferable over the more traditional tools, such as ESM, except when the intervention aims exactly at creating awareness about one's emotions.

In both cases, the choice of monitoring device or tool must be taken carefully, taking into account the different properties that are relevant to the individual user. When, for example, a common tool like ESM is used, special attention should be given to the interpretation of the results. Measuring any type of behavior or human attribute in daily life is challenging, due to missing and noisy date; conventional statistical methods have difficulty in dealing with this type of data. Advanced data mining and machine learning methods, such as personal networks, are emerging as promising tools to continuously learn about the individual's behavior and its changes over time.

A proper understanding of daily life data is an important prerequisite for effective interventions in active and healthy ageing, but the data must be used in a fitting decision-making process, or coaching strategy. From the field of psychology and persuasive system design a host of different methods and strategies have emerged over the past decades. For any coaching strategy, personalization is an important factor that needs to be taken into account into the design of the system. Many different strategies for tailoring the communication to the individual user exist and are most often straightforward to implement.

The implementation of smart monitoring, reasoning and coaching techniques into an application that can add value to the lives of the users can happen in many different ways. Mobile applications, web sites, virtual reality worlds, or even personal robotic, or holographic companions are some of the embodiments that a coaching service can take. We have reviewed a small number of examples of such applications in line with the Persuasive System Design model. The most important conclusion is that, to be effective, the individual's needs and preferences must be the foremost driver for any design and implementation decision. To guarantee the success of interventions promoting active and healthy ageing, stakeholders must work together combining expertise from different fields. Moreover, the advent of Internet-of-Things, 5G Networks, and the idea that all devices are connected will bring new opportunities inside and outside the home environment. Mobile cloud computing also ensures that all information is available all the time, everywhere. Also, with new smart devices, reasoning on large datasets becomes possible at any moment and time.

There is also the question of the technology affinity. The idea that older adults are technology avoiders is not always correct, and besides this is at *worst* a temporary concern as in the developed countries the next generation(s) of 65+ did already grow up with technology in their lives. Although technology continues to develop at an even faster pace, the expectation is that the ability to adapt to new technologies is increasing with current and future generations as well. Furthermore, in our overview we have found no indication for general rules concerning the design for older age; instead, as within any other age group, physical and cognitive abilities, motivation and contextual factors should be the main motivator for design decisions. Predicting what the future of technology in the support of healthcare will bring is threading on thin ice. However, through the combination of unobtrusive monitoring techniques, ever more effective reasoning, coaching strategies combined with persuasive technology and applications designed for real users, we might be one step closer to true personalized medicine. We look at a bright future in which technology supports the older adults in being active and engaged in their communities, not only being part of, but a structural pillar of their communities, for as long as possible.

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7. References

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