Towards Pervasive Predictive Analytics in Interactive Prevention and Rehabilitation for Older People

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Abstract. The world population is rapidly aging and becoming a burden to health systems around the world. In this work we present a conceptual framework to encourage the research community to develop more comprehensive and adaptive ICT solutions for prevention and rehabilitation of chronic conditions in the daily life of the aging population and beyond health facilities. We first present an overview of current international standards in human functioning and disability, and how chronic conditions are interconnected in older age. We then describe innovative mobile and sensor technologies, predictive data analysis in healthcare, and game-based prevention and rehabilitation techniques. We then set forth a multidisciplinary approach for the personalized prevention and rehabilitation of chronic conditions using unobtrusive and pervasive sensors, interactive activities, and predictive analytics, which also eases the tasks of health-related researchers, caregivers and providers. Our proposal represents a conceptual basis for future research, in which much remains to be done in terms of standardization of technologies and health terminology, as well as data protection and privacy legislation.

Keywords. Data collection, Telerehabilitation, Computer-Assisted Therapy

1 Introduction

Rising life expectancy and lower birth rates are the main causes of the world population's aging, especially in the most economically developed countries offering widespread access to healthcare. However, older people (ages 65 and above) are more likely to develop co-morbid conditions that impair their cognitive and physical functioning [1], negatively affecting their Quality of Life (QoL) and increasing the burden on health systems. Due to the complex nature of these chronic conditions, most research studies focus on one or at most two chronic conditions at the same time. Unfortunately, the interconnection and frequent co-occurrence of these conditions makes it difficult to obtain an accurate description of the pathology and treatment of a single condition, especially in older adults. Recent advances in information and communication technology (ICT) allow us to develop innovative solutions for assistance, prevention and rehabilitation used for and by older people, such as sensor technology [2] and virtual reality [3]. In addition, the convergence to connected devices and services via the Internet of Things (IoT), Cloud computing, and Big Data techniques allow us to rapidly collect and analyze enormous volumes of diverse and valuable data like never before. Moreover, it is now possible to use these technologies to develop predictive and adaptive interventions for personalized healthcare.

Therefore, as stated in a previous paper [4], we believe that it is necessary to move forward and combine these advances in ICT to create a more holistic approach for healthy aging in terms of prevention, minimization of negative effects, and rehabilitation of chronic conditions beyond the walls of health facilities. Moreover, we think that the shift of data collection and analysis from health facilities to the daily-life activities of older people (e.g., at home, at the workplace, on the move) will increase their empowerment and reduce the burden on society health costs. In this work, we give a more detailed overview of the motivations, technologies and standards of our proposed conceptual model to attain this goal, which is based on established and internationally validated concepts of human functioning and disability.

2 Health conditions and functioning level in older age

The health status of a person is determined by decisive contextual factors inherent to the individual (personal factors), as well as to their socio-economical and physical environments (environmental factors). In particular, contextual factors associated with the increased rate of an ensuing disease (or condition) are defined as risk factors for that condition. These contextual factors can be further classified into modifiable and non-modifiable, according to the individual possibility of change. Nonetheless, sometimes this classification is not straightforward. For instance, some factors that are traditionally considered non-modifiable can be controlled, or as demonstrated by studies in epigenetics their effects can be reduced by environmental changes [5]. Modifiable behavioral determinants are of particular research interest because they can influence the effectiveness of preventive, curative and rehabilitative modes of intervention for healthy aging [6]. For instance, smoking status, physical activity level, body mass index, diet, and alcohol use are lifestyle factors associated with health status in older age [7].

People's health determinants (illustrated in Fig. 1), and consequently health status, change over time; thus, people's functioning level does not remain constant, and they may experience some form of disability in their life. To classify this level of functioning, the World Health Organization (WHO) developed the International Classification of Functioning, Disability and Health (ICF). This standard was born from the need to interlink health information systems in a common and accessible manner, to compare data across systems, disciplines and countries. ICF provides a framework for classification regarding people's body function and structure, what individuals with a health condition can do in a standard environment (level of ability), and what they actually do in their usual environment (level of performance). In ICF, disability and functioning are viewed as outcomes of interactions between health conditions (diseases, disorders and injuries) and contextual factors (personal and environmental).

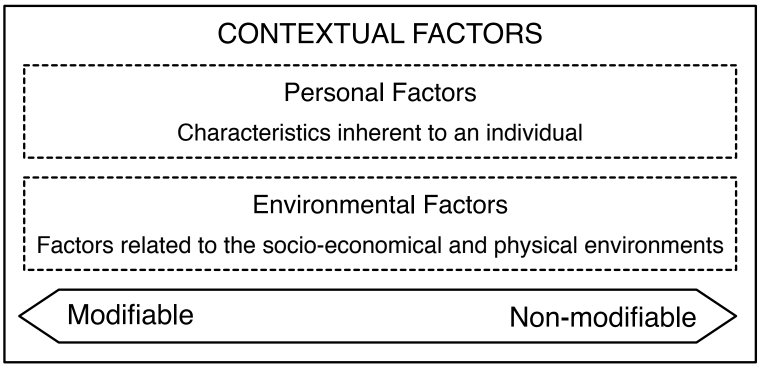

Fig. 1. Health determinants are decisive contextual factors that affect our health

ICF does not classify people but describes their functioning profiles, which are not derived from diagnostic criteria. In this sense, it is complementary to the International Classification of Diseases (ICD), the standard diagnostic tool for epidemiology, health management, and clinical purposes. Both standards help monitor people's health information, in terms of disease and other prevalent conditions, as well as the impact of interventions in the experience of functioning, even when the medical diagnosis remains unchanged. For instance, two people may have the same chronic condition, as described by ICD, but different functioning levels, as described by ICF. Moreover, this functioning level may change over time in the same individual and chronic condition. For instance, Fig. 2 illustrates how the ICF classification could be applied to hypertensive heart disease with heart failure. The figure shows the most significant categories of body functions and structure, activities and participation, and environmental factors related to heart disease, based on the empirical evidence for a core set of related CVD [8]. All the elements have their classification code, except for personal factors, which are not classified in ICF. This example also illustrates how core sets of ICF can be used for specific chronic conditions to monitor the functioning of older people in a standard way.

Specifically, ICF enables data collection on levels of functioning and disability in a consistent and comparable manner in prevention and rehabilitation medicine [9]. Furthermore, given the broad scope of ICF, core sub-sets are continually being developed and tested for specific purposes, such as the ICF Rehabilitation Sets [10], which could also be used in interventions for chronic conditions in older adults. Therefore, ICF offers a standard classification to monitor the functional evolution of older people with these and other chronic conditions, many of which are co-occurring. Indeed, various reports estimate the comorbidity prevalence in economically advanced countries for people aged 65 years and over to be around 50%, with cardiovascular diseases (CVD), Alzheimer's disease (AD) and depression being among the most common chronic conditions [11]. Moreover, CVD, AD, and depression can even lead to or be aggravated by accidental falls in older adults.

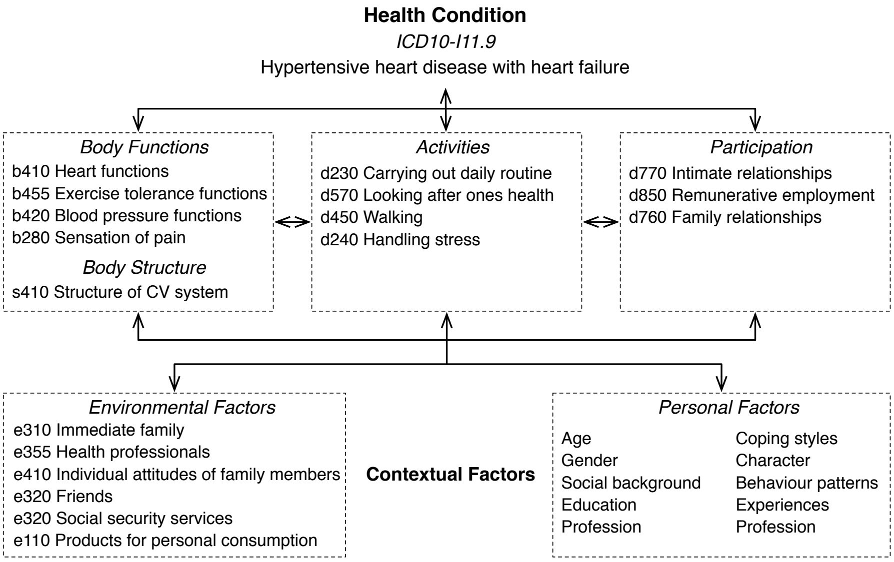

Fig. 2. Example of an ICF classification for a CVD condition

That being the case, CVD, AD, depression, and falls form an interesting example of a comorbid group of conditions because they are prevalent in older age, they disturb both physical and mental wellbeing, and there is a significant association among them. For instance, CVD and AD often lead to depression [12], with an incidence of around 25% in people with dementia [13]. Still, the association between AD and depression can be very complex, as depression is considered both a symptom of and a risk factor for AD [14]. Conversely, several studies have determined that depression is also a major risk factor for the development of CVD [15]. For instance, rates of strokes in older people can be 2.3 to 2.7 times higher in people with high levels of depression [16]. Gender may be also a significant risk factor for these conditions. For example, women are more likely to suffer depression than men, especially in older age [17]. The prevalence of AD is 40-60% among women aged 30 and over; among men the proportion increases from around 20% at age 30 to around 70% at ages 95 and over [18].

Constant intellectual, social and physical activities reduce the risk of CVD, AD and depression [19]. However, falls with injury, which are common among older adults, may hamper such activities. Thirty per cent of people over 65 and 50% of those over 80 fall annually, with women having a double lifetime risk of fracture compared to men, mainly due to osteoporosis [20]. This prevalence of falls is caused by physical, sensory, and cognitive changes associated with aging. During a longitudinal study on the main consequences and risk factors among older fallers, it was found that more than one-third suffered functional decline after falling [21]. In addition, female gender, higher medication use, depression symptoms and fall injuries were the most significant risk factors for functional decline after falling. Nonetheless, it is important that intellectual, social and physical activities continue to be carried on before, during, and after the onset of chronic conditions in older age. For this reason, interventions should induce positive behavioral changes that stimulate these activities and that promote a healthy lifestyle.

Incidentally, ICF mentions the importance of lifestyle and health-related habits (HrH) as personal determinants, but it does not offer their precise definition. To fill this gap, the Spanish Association for the Scientific Study of Healthy Aging has developed a taxonomy for the evaluation of HrH in primary care, in the context of the project eVital [22]. This taxonomy was composed by a panel of experts and is based on the conceptual model of ICF. The experts agreed on six main HrH categories for health evaluation: diet/exercise, vitality/stress, sleep, cognition, substance use, and other health habits. Of these main HrH, three are directly linked to motivation to change and should be the target of behavioral change techniques (diet/exercise, substance use, and other risk habits); the other three are less related but its monitoring is important nonetheless (cognition, vitality/stress, and sleep). In this regard, and thanks to the increase in commercial interest on Internet of Things (IoT) health monitoring technology for older people, it is now feasible to monitor and collect sufficient health-related data to predict outcomes and personalize health interventions.

3 Technologies and strategies for health monitoring and intervention

The IoT is a paradigm that considers the pervasiveness of a variety of objects connected via wire or wirelessly, which interact with each other to offer new services in creating a smart environment. In recent years, the convergence to ubiquitous services envisioned by the IoT has been accelerated by the massive adoption of smartphones, which act as hubs for many of the current connected objects. Indeed, the smartphone has become the key for IoT-based health services beyond the current concept of mobile technology for healthcare (mHealth). Given the immense market opportunities, mobile personal health monitoring (PHM) has attracted the interest of Google, Apple, and Microsoft. Each one of these companies has started offering its own ecosystem of health-related platforms, PHM services, and wearable devices and technologies. Besides, several other companies offer related (and compatible) products and services, such as consumer wearable devices, Global Positioning System (GPS) tracking, smart weight balances, and other non-wearable devices to monitor personal health and behavior.

These technologies could improve the current approaches to Remote Patient Monitoring (RPM): to collect, transmit, and evaluate the patient's health data; then to notify stakeholders when a problem based on the evaluation is detected, and eventually to intervene with an appropriate treatment or to modify a HrH. RPM is not necessarily focused on older people, but it has been integrated into the broader concept of Ambient Assisted Living (AAL), which allows older people to live in complete or partial autonomy. Moreover, AAL can aid in preventing, curing, and improving the health status of older adults [23]. The data collected from AAL systems can be integrated into the vast health system records, which could be used to automatically learn and make decisions [24]. Furthermore, predictive analytics, using innovative statistical models and techniques, allow analyzing such huge volumes of data to make predictions about the future [25].

The use of predictive and intelligent data models has many applications in healthcare, ranging from metabolic modeling, gene expression, quality of care assessment, and processing from domestic monitoring systems [26]. Current risk score and models can be automatized to predict the risk of developing certain conditions or their worsening. For instance, SCORE (Systematic COronary Risk Evaluation) is a risk scoring system used in the clinical management of cardiovascular risk in Europe to estimate fatal CVD events over a ten-year period [27]. InterHeart is a more geographically wide study, from which the InterHeart Modifiable Risk Score was developed and validated for an international population [28]. Most interestingly, new predictive models are being developed thanks to domestic monitoring systems, such as using machine learning for early detection and prediction of illness in older people [29]. In this context, machine learning refers to computers that can learn and make predictions from data without an explicit program. This is in contrast to experts systems, in which decisions are made according to an algorithm based on the knowledge of experts in the given domain, also used to asses the health status of older people [30]. Both approaches can be used in combination or under different scenarios, although machine learning is particularly apt for prediction when huge volumes of data are available.

ICT also allows us to monitor and improve the level of functioning and participation through interactive activities. Some examples of interactive activities are e-mail, web browsing and videogames. The last example is frequently related to virtual reality (VR), an immersive computer multimodal environment. There are different degrees of immersion in the Reality-Virtuality continuum, ranging from none (real environment) to fully immersive (virtual environment), with mixed reality (MR) in between. Naturally, one of the main advantages of immersive VR activities is the possibility of completely adapting the virtual environment of the user and thus offer a personalized experience to monitor or induce a change in HrH. Interest in VR has recently spiked, given that competitive commercial solutions are becoming available to individual consumers. These range from simple add-ons for smartphones (Google Cardboard and Samsung Gear VR), to much more advanced headsets for videogame consoles (PlayStation VR), personal computers (HTC Vive and Oculus Rift), or even smartphones (Google Daydream). Microsoft also works on an immersive headset, HoloLens, intended for augmented reality applications. This commercial expansion will certainly benefit the development of VR for healthcare, with many applications from medical visualization to rehabilitation therapy and serious games.

Serious games are interactive games that are specifically designed to elicit a positive change in the player, such as HrH, including physical and mental wellbeing [31]. For instance, *exer-gaming*, in which the gameplay involves significant physical exercise, can help older people with depression, balance issues, dementia, and CVD. Other kind of serious games can also improve cognitive control in older age [32]. On the other hand, in gamification, game design elements are used in a non-game context [33] to engage people in certain activities by making them entertaining and rewarding, based on intrinsic and extrinsic motivators. For example, an activity gameplay could use narrative elements to entertain, and mechanics could be based on any combination of skill, luck, and strategy. Games and gamified activities can be played alone (single-player) or with others (multi-player), either cooperatively or competitively, or both. In addition, game-based activities can complement traditional AAL systems to enhance the autonomy of older people at home [34].

4 Pervasive predictive analytics for healthy aging

Based on the benefits of the aforementioned concepts, we propose a pervasive ICT-based conceptual model to monitor, analyze, predict and improve older people's functioning levels and HrH for the prevention and rehabilitation of chronic conditions. This framework would provide data-driven personalized activities and recommendations that are accessible and adaptive to older people. The objectives of this framework are: 1) to promote self-management of prevention and rehabilitation; 2) to provide tools and mechanisms that aid in care provided by close relationships (e.g., family and friends); 3) to enable a better understanding of older people's health by the community (e.g., medical personnel, researchers, policy makers); 4) and to encourage the older individual's participation in society. This framework consists of four main parts: Remote Monitoring (RM), Predictive Analytics (PA), a User Online Platform (UOP), and a set of Interactive Activities (IA). Key risk indicators (KRI) would be selected according to the corresponding predictive models for the target conditions and factors. These KRI refer to health determinants and the functioning level of the users measured through the interactive activities.

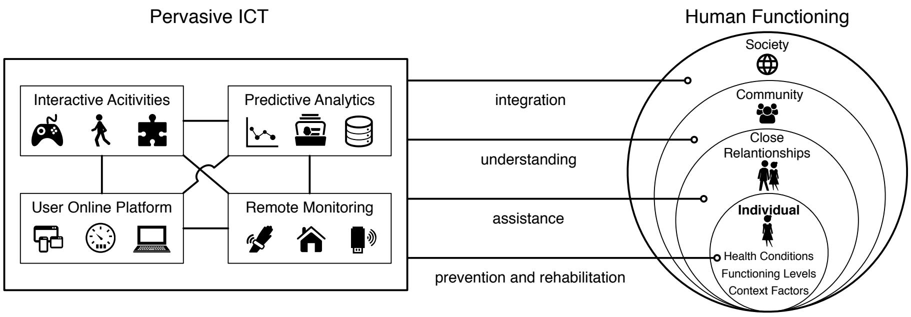

Fig. 3. Conceptual model of the proposed approach for healthy aging through pervasive ICT

Most data would be collected unobtrusively via RM, using sensors for domestic and personal use, such as fixed and wearable sensors. Other data would be collected via the interactive activities themselves, such as the performance of a given VR rehabilitation exercise. The UOP would also allow collecting other KRI, such as periodic self-assessment and risk score questionnaires, and it would allow the end users or authorized third parties (e.g., family and physicians) to monitor the current health status and receive alerts. The UOP should be user-friendly, accessible and available from both desktop and mobile devices. The UOP would also be the gateway for the set of IA and related KRI. At the beginning, the end users would have access to a common set of activities designed to maintain the overall levels of physical and mental wellbeing related to the users' age. As the health determinants, health status, and HrH of the end users evolve, the interactive activities would automatically adapt according to the analysis and prediction made by the system. To engage and entertain end users, many of these tasks would consist on activities such as MR videogames and gamified activities, besides non-game activities like online social media and other kinds of interpersonal communication. The intention is to stimulate social participation and increase the interest of the users in intellectual and physical activities to incorporate positive HrH, reducing the risk of chronic conditions. All of the end users' data from the RM, IA, and UOP would be harmonized for PA to further personalize these parts of the system.

PA would be used to analyze and detect physical or behavioral changes, based on the predictive models. With this approach, specific risks might be minimized as soon as they are detected by the system. At the same time, the progress or regress of rehabilitation therapies could be evaluated as they are applied. If the system detects significant risks or a decrease in functioning levels, an alert would be emitted to the concerned end user, close relationships, and medical personnel. Although the system would automatically monitor and personalize these aspects, it is still crucial to ease the involvement of other key stakeholders. For this reason, the UOP would provide access and ease the daily tasks of authorized care providers (physicians, nurses, etc.) and caregivers (family, friends, etc.) to follow the health evolution of the end users. Other authorized third parties could also have access to anonymized data for research, statistics and management purposes. For example, researchers could analyze the data to study and discover patterns, causes and effects of health conditions across different categories, or discover possible socio-behavioral patterns, etc. As might be expected, a strict access control policy for each role would be established to respect the privacy of the patients and other sensitive information, in compliance with the corresponding local legislation. Regarding the stakeholders that would directly interact with the different parts of the framework, we identify the following four main roles:

- End user: This is the main stakeholder in the framework. The end user is an older person who wants to improve his or her health status by improving the own health-related habits, either for prevention or rehabilitation. The end user is also the primary stakeholder in the RM part of the framework, which automatically collects the necessary health-related data. In addition, the end user can interact with the UOP, either to collect additional data or for self-monitoring, as well as a gateway to the IA.
- Caregivers: A caregiver is a person who helps the end user in his or her activities in daily life. Usually the caregiver is a close relationship, such as a family member, but sometimes it can also be a paid person. Caregivers would be able to accompany the end user in their utilization of the RM and execution of IA, and they would also have personalized access to the UOP to monitor or receive alerts on their corresponding end user.
- Care providers: These are health professionals that offer preventive, curative, or rehabilitative health services to the end user. As with the caregivers, care providers would have a personalized access and alerts regarding the data of their end user or group of end users through the UOP. However, care providers would have access

to a more comprehensive set of functionalities to monitor the health of their end users.
- Researchers: The researchers are professionals from different scientific disciplines (e.g., clinicians, gerontologist, psychologist, sociologists, and computer scientists) who are interested in the inner workings and improvement of all of the parts of the framework, particularly the tuning of the PA.

Of course, in addition to these roles, there are other important stakeholders (e.g., policy makers) that determine the health status of older people, but these are influenced by the four roles identified above, instead of interacting directly with the parts of the framework. Besides, the proposed framework is also independent of the underlying approaches, technologies, and implementation chosen. The RM could be implemented using Bluetooth, ZigBee or other standard for wireless sensor networks; the UOP could be accessed via native applications for mobile systems, desktop environments, or special units; the IA could be serious games or other gamified activities across the reality-virtuality continuum; and the PA could use diverse approaches (or combinations of) for predictive modeling and analysis such as expert systems and machine learning. These technologies and standards are rapidly evolving; nonetheless, we believe that the principles of the proposed framework serve as a high-level conceptual model for future research.

5 Conclusions

We have described how chronic conditions in older age are prevalent and interlinked, the benefits of using international standards to classify the functioning level of these conditions, and how ICT could be applied to prevent and rehabilitate through pervasive predictive analytics. Our proposed data-driven approach is a cohesive combination of these concepts that aims to move forward current implementations of PHR and AAL in older people. Nonetheless, several issues need to be tackled before a successful implementation based on this approach. For instance, there are no universally adapted open standards for health data, IoT and VR technology, although academia, industry, and standardization bodies are working on this issue. In addition, the disparity around the world concerning legal frameworks regarding data protection and privacy is another critical issue, but one that is beyond the scope of the present work. Given that our approach implicates the collection of highly sensitive data and the profiling of older people's functioning, we need to implement secure transmission and to control access to these data to avoid their misuse. Despite these current shortcomings, we believe that our framework could be used as a conceptual basis for future research on prevention and rehabilitation of chronic conditions in older age through pervasive, predictive, and personalized health solutions.

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