A Conceptual Model of Health Monitoring Systems Centred on ADLs Performance in Older Adults

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Abstract. Older adults usually present physical and mental problems such as anxiety, stress, depression, and mood disorders. In addition, there is a strong correlation between emotions/socialization and health. Negative emotions affect mental and physical health and can be caused by other diseases. Social isolation is a health risk factor comparable to smoking or physical inactivity. The diagnosis process is usually time-consuming and requires resources. The performance of the Activities of Daily Living (ADLs) could be used as an index of the decay of the elders, which can be delayed. ICTs can provide valuable and automatic support to health professionals facilitating routine tasks. Health monitoring systems, especially multi-sensing and intelligent, should be designed to fulfil requirements from each specific health domain. This paper reviews state-of-the-art and proposes a conceptual model centered on the ADLs concept, considering different health dimensions (social, emotional, physical and cognitive). Our proposal allows the evaluation of the elders' health holistically, and transparently. The conceptual model provides comprehensibility for this domain and provides a basis for developing multi-sensing and intelligent health monitoring systems.

Keywords: Health Monitoring, Activities of Daily Living, Conceptual Models

1 Introduction

The World Health Organization (WHO) defines the quality of life as "an individual's perception of their position in life in the context of the culture and value systems in which they live, and in relation to their goals, expectations, standards and concerns" [1] For the older adults, good quality of life means living independently and feeling good while carrying out Activities of Daily Living (ADLs), considering physical, psychological, and social aspects of life [2]. Therefore, collecting information about physical, social, and cognitive areas is necessary to promote active and healthy ageing and provide people with an independent life for a longer time [3].

The early detection of behavioral changes and risk factors of functional decline can prevent problems in ageing. For example, detecting aspects restricting participating in the ADLs may be crucial to prevent reversible factors that different health agents such as physicians can approach. Depressive and anxiety symptoms are usually present in the elderly and cause a decrease in the quality of life in this population, favoring social isolation and the appearance of other clinical diseases. The ageing process associated with a sedentary lifestyle also favors mental, social, and physical issues because this may cause physiological changes such as muscle strength, aerobic capacity, and motor impairments. These aspects lead to a decrease in the capacity to perform ADLs efficiently and with independence [2]. Diseases such as frailty and dependence can be predicted by observing when older adults reduce their performance level in ADLs [4]. Moreover, the ADL concept entails a holistic perspective because of the different dimensions (cognitive, social, emotional, etc.) required for performing these activities. Another interesting property of the monitoring of the performance of the ADLs is the ecological perspective. The term "ecological" refers to observe the person-in-the-environment (during their daily life) i.e., outside the laboratory or clinical setting. ADLs assessment interacts less with the daily life of older adults than traditional assessments, saves time, associated cost and is more efficient spending the health system resources.

Nowadays, there is an interest in political and research areas to improve the quality of life of elderly people. However, the previous observational studies and experiments are focused on isolated aspects of health, and the literature is limited in scope. Several conceptual models are proposed, but none of them center the evaluation system on the ADLs, considering different dimensions of health. Recent ICT technologies use mobile/wearable devices, platforms and systems, and data analytics. They are currently known as multi-sensing, intelligent systems. They collect data from sensors providing physiological information related to health (e.g. heart rate, skin temperature, movement, etc.) and from devices providing context information (e.g., presence in a room, geo-positioning, atmospheric pressure, etc.). These systems are ad hoc solutions for addressing some of the mentioned aspects or properties.

Conceptual Modelling has been recognized as an important method to manage complexity and, particularly in the fields of system analysis and design. Conceptual models have been used to provide formal (or semi-formal) representations of relevant aspects of the physical and digital realities. However, some works claim the need of reconceptualization of conceptual modelling in light of changing and emerging requirements nowadays [5]. One of these emerging requirements is to understand human needs and how design responds to these needs, i.e. human-centered design [6].

This paper reviews the state of the art and proposes a conceptual model centered on the ADL concept. The aim is to take into account the different dimensions (social, emotional, physical and cognitive), required for performing the ADLs. This conceptual model shapes the evaluation of the elderly's health holistically and ecologically, extending previous models found in the literature. Furthermore, this model deepens the knowledge of this specific domain and serves as a basis for developing intelligent and multi-sensing health monitoring systems.

The paper is organized as follows. Section 2 presents foundations focused on the important aspects of elderly people's health monitoring and ADLs. Section 3 reviews related work. Section 4 presents the proposed conceptual model and instantiation example. Finally, Section 5 summarizes conclusions and introduces future research.

2 Foundations

The term ADLs involves all activities performed by human beings during their lifespan. One of the most accepted classification for ADLs is based on their level of complexity. This classification organize activities from the basic (BADL) (e.g. self-care activities, functional mobility, and the care of personal devices), through the instrumental (IADL) (e.g. use of the phone, shopping tasks, and use of transportation), and up to the advanced (AADL) (e.g. planning travels, and participation in events and meetings). Each ADL requires different body functions and structures from different dimensions (physical, cognitive, social and emotional). IADLs require cognitive and motor complexity (executive functions), and imply an interaction with the social environment that surrounds the persons [7[. AADLs are the most complex ADLs as they involve voluntary physical and social functions, but are not essential to maintain independence. The performance of IADLs is an important health indicator to predict mild or severe cognitive impairments, such as dementia in older adults [8].

Health systems can evaluate the health status by observing people's movement and exercise intensity, recognizing ADLs indoor and outdoor, and even detecting food intake, interactions with relatives and friends, etc. The identification of risks and anomalies is important to help the elderly and caregivers to prevent dangerous situations [3]. Health systems based on intelligent systems aim to reduce hospitalized demands and costs. They include sensors that allow the continuous monitoring of different aspects of health such as the vital parameters, physical activity and falls [9].

Sensors and devices with sensors, such as wearables and smartphones are used to monitor biological, behavioral, and environmental data of people, because they are non-invasive, easily acceptable by subjects, and do not intrude users in their normal activities [10]. The most common sensors used in health are [9]: electrodermal activity (EDA), photoplethysmography (PPG), electrocardiography (ECG), electroencephalography (EEG), and skin temperature (SKT), among others. They collect physiological data such as heart rate, blood pressure, body temperature, respiratory rate, and blood oxygen saturation. Other physical reactions can also be measured with video or infrared cameras, microphones and electromyograms (EMG), for example, facial and body gestures. They can be combined with technologies to identify the dynamic position of people: Radio-Frequency Identification (RFID), Bluetooth Low Energy (BLE) or beacons, GPS, accelerometer (ACC) and gyroscope (GYR). Environmental sensors and sensors embedded in furniture, home appliances, walls and carpets also help to gather contextual information useful to know the user's behavior. Once the sensors collect the data, it is necessary to analyze it to infer relevant information. Machine learning (ML) techniques are common in these situations because they provide better accuracy with big quantities of sensory data than other statistical analyses [11]. In particular, ML has been used to accurately recognize activities, detect health risk factors and specific health conditions such as frailty or dependence [12][13].

There are some important challenges in the development of the health monitoring systems: usability improvement, low cost-based solutions, data security guarantees, integration of devices, quality data collecting and processing, managing big data, and device power consumption [14]. Conceptual modelling could be useful to analyze systems complexity and also to estimate the strategy behind the development of the software and the best devices to be used. Some of those challenges can be addressed by including them in the model.

3 Related work

Several initiatives tried to model the sensor environments, and even some standardization bodies have proposed their solutions [15]. It is a field in continuous evolution and the reuse, evolution and extension of previous models is a common practice. One of the main initiatives is the Semantic Sensor Network model (SSN) by W3C, which gathered all sensor models at that time and developed a complete semantic model centered on the concept of the sensor [16]. It also includes other concepts and relationships between them, such as sensor properties, systems, deployments, stimuli, and observations. Other models evolve by extending SSN, such as IoT-A [17], which introduces the concept of service, resources, and entities, or SAO [18], for data analytics and event detection.

However, with the proliferation of sensors and stream data, SSN was too heavy to effectively process IoT data. Then, other initiatives move to the lightweight models. For example, IoT-Lite [19], which also introduced the concepts of actuators and coverage. LiO-IoT [20] that extends IoT-Lite adding Tag concepts and relationships. IoT-Stream [21], which deals with analytics. Even W3C updated its SSN with a core model less heavy, Sensor, Observation, Sample and Actuation (SOSA) [22].

Other models complement the sensor models with concepts needed to annotate the sensors and specifically the sensory data. For example, location models, such as Geo[1] locate the sensors or data. Geo is composed of a few basic terms, such as latitude, longitude, and altitude. GeoSPARQL is a standard for the representation and querying of geospatial data from the Open Geospatial Consortium (OGC) [23]. GeoJSON[2] is another example that describes geographic features, and geometric forms, such as Point, LineString, Polygon, MultiPoint, etc. Time ontology[3] represents topological (ordering) relations, duration, and temporal position (i.e., date–time information) with different time references (unix, geologic time, etc.).

All these models need taxonomies, which categorize the different devices, activities, etc. For example, some taxonomies of sensors describe the characteristics of sensors: power, configuration, material, sensing methods, functions, etc. [24]. The QU[4] model focuses on quantities and units and supports different Systems Modelling Languages (SysML) users. Even some initiatives perform a step further and do not only create the taxonomy, but divide the taxonomy in levels. For example, [25] present a wristband

1 https://www.w3.org/2003/01/geo/
2 https://tools.ietf.org/html/rfc7946
3 https://www.w3.org/TR/2017/REC-owl-time-20171019
4 https://www.w3.org/2005/Incubator/ssn/ssnx/qu/qu-rec20.html)

taxonomy in three levels: the tracking raw input (sensory data), the raw output (devices and HW), and the intelligent output (high-level events).

Dealing with sensory data is usually noisy and faulty, so we need to model as well the Quality of Information. The common quality concepts modelled are Completeness, Correctness, Concordance, Currency, Plausibility [26] and Security [27], access control in cloud data [28] and the provenance of the data, PROV-O [29]. Even Zero model [30] uses blockchain to assure the security and traceability of data.

In the field of heath, Health Level-7 (HL7) regulates the digital transfer of clinical and administrative data. It is a set of international standards and guidelines which provides a common vocabulary in order to interoperate between the endpoints. One of these standards is the Fast Healthcare Interoperability Resources (FHIR) (https://www.hl7.org/fhir/index.html), which divides the concepts into seven levels. Level 1 provides the basic framework, mainly data types and formats. Level 2 deals with implementation and binding to external specifications, with concepts such as versions, databases, security. Level 3 defines the patients and other concepts of healthcare systems such as devices, locations, etc. Level 4 annotates the records and processes, such as diagnosis, medication and financial issues. And level 5 provides the reasoning, modelling concepts such as actuation plans.

Although several initiatives have already merged all the concepts mentioned above [31], SmartEnv has applied them to older adults. SmartEnv extends SSN and represents different aspects of smart and sensorized environments [32]. These aspects are: observation/sensing, agents, activities/events, objects, network set-up, spatial and temporal aspects. The model annotates autonomous health systems used for elderly homes.

Regarding ADLs, [33] models regular activities performed in a house, with actions and concepts. For example, calling someone, etc. But it only models some activities and no instrumental activities. [23] models the human activities in smart homes, emphasizing the time sequence, i.e. whether the activities are sequential or concurrent. Additionally they use rules to detect activities, for example sleep takes place in bed and has a duration of 8 hours.

4 A Conceptual Model Centered on ADLs Performance

We propose a holistic and ecological model for health focused on the monitoring of ADLs performance with sensors and data analytics. This model extends and reuses the models presented in section 3, borrowing some concepts and relationships. Fig. 1 shows the general overview of the model, and Fig. 2, the important concepts and relationships.

Our model has 3 layers: hardware, software and domain.

The **hardware layer** includes the devices (e.g., wearables, mobile phones) and sensors used to collect data and to show information to the users. Table 1 shows one column for each concept: devices, sensors and characteristics. A device can have several sensors embedded or connect with other external sensors, receiving data from them. As section 2 shows, there are several types of sensors, although we have represented the most commonly used in health: physiological and environmental sensors.

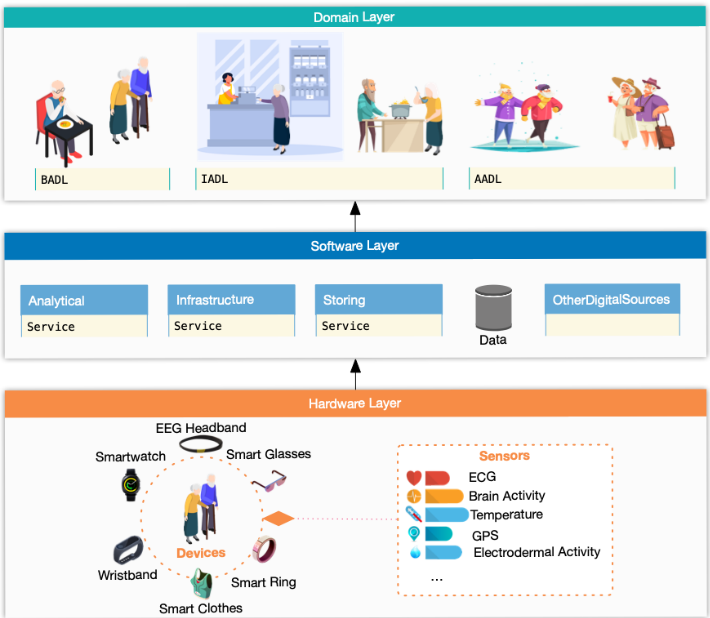

Fig. 1. General overview of the conceptual model

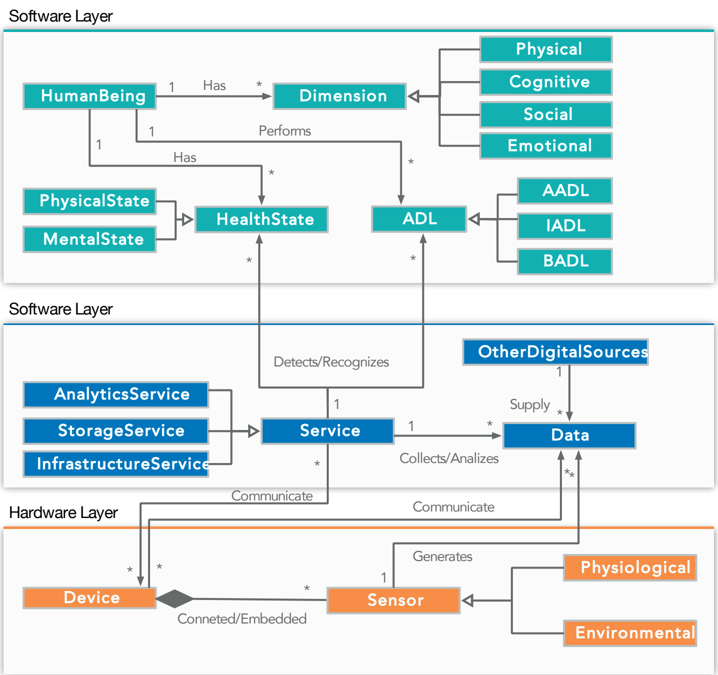

Fig. 2. Conceptual model

Table 1. Characteristics of core concepts of the hardware layer

Device	Sensor	Measuring capabilities
Name	Name	Coverage
OperativeSystem	Domain	Latency
NetworkConnectivity	Configuration	Accuracy
Screen	Power	Frequency
Battery	SensingFunction	Resolution
Memory	SensingMethod	Sensitivity
ComputingPower	Material	Selectivity
	ObservedProperty	Precision
	StimulusDetected	ResponseTime
	Type	DetectionLimit
		inCondition

The **software layer** consists of data that are generated by sensors, communicated by devices or supplied by other digital resources such as external services (See table 2). Each data has a timestamp, type, rank, value and several quality attributes. This layer also includes a set of services that manage data. There are specific services to communicate data between devices and servers, in which the services are deployed. Most common communication services implement request/reply (point-to-point communication) or Publication/Subscription (many-to-many communication) paradigms. Other specific services are specialized in data storing, for instance, data could be stored in a non-SQL database (local or cloud).And other analytic services process the data which usually apply machine learning techniques to identify or classify health status. The results of the analysis are sent to the devices used by elders or caregivers.

Table 2. Characteristics of core concepts of the software and domain layer

Service	Data	ADL	Health state
Name	Timestamp	Name	Factor
Type /Method/technique	Type	Type	Type
Parameters []	Value	Description	Rank
Performance indexes[]	Rank	Place	Value
	Format	Time sequence	Health state
	Quality attribute []	Measurements[]	Factor

The **domain layer** represents the human beings and the information related to their health status and the ADLs performance. There are three types of ADLS: AADLs, IADLs and BADLs. Each ADL has a name, a description and is performed in a place or a space (indoor or outdoor). Besides, an ADL can be carried out at the same time as others or sequentially (time sequence) and has different aspects that can be measured to assess its performance (e.g. Motions, Gestures, BodyAcceleration, Proximity, Duration, Intensity, etc.). We differentiate between two types of physical and mental health status, with different values for each health factor. Besides, human beings can be observed from different dimensions, (physical, cognitive, social and emotional). Table 2 also shows the main characteristics for the core concepts of this layer, ADL and Health state.

5 Conclusions

The decay in the elderly, which can be delayed or reversed, affects not only the physical dimension of health but also the cognitive, emotional, and social dimensions. We could consider all these dimensions by monitoring the elderly during their ADLs. Additionally, this monitoring is holistic and ecological. Systems using sensors and data analytics can help in the automation of the health assessment by monitoring the performance of the ADLs.

We have performed an extensive review of state art in the area, and we can conclude that several proposals could model parts of the proposed systems. However, none of them provides all the concepts and relationships we need, and none centres on the ADLs performed by the elderly. We have used several concepts and relationships from the previous literature in our solution. We have added the missing parts and linked them together. Our model extends the literature by completing a comprehensive model to monitor health by evaluating ADLs performance. The model provides support to the ecologic and holistic evaluation.

Hence, a holistic and ecological evaluation system for monitoring elderly people can be established by using observations of the elders in their natural contexts during the performance of the ADLs involved in their routines. This novel monitoring system may serve as a form for the evaluation of multiple health's aspects at the same time, reducing time and cost for the health system and professionals. Additionally, the behaviour of elderly people under evaluation is expected to be more accurate/precise about the real health status due to the reduction of multiple possible biases happening during the evaluation of the person in a clinical setting. The conceptual model presented in the current work covers all the relevant elements to develop this monitoring system. Our model could serve as a basis for developing ecological and holistic health monitoring systems that consider several dimensions of health. These systems help health professionals to automate the assessment of the health status. In the future we want to validate the proposed model implementing a monitoring system and performing an extensive experiment with elderly people.

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