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User-Centered Rating of Well-Being in Older Adults

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ABSTRACT Predictions estimate that the future will entail several devices related to IoT (Internet of Things). Most of these will be present in our homes, collecting useful information and triggering informed actions. Much work has been done on collecting data and triggering such devices. However, there is not much work on how to make use of such information to measure the well-being of a person. In the context of older adults, it would be useful to define a means to estimate their well-being, provide them some feedback, and eventually share it with a family member or caregiver. This article emphasizes how to measure well-being through a user-centered Personal Well-being Rating (PWR). Although the proposed rating is idealized as a general equation, our case study is mainly centered on older adults. These are undeniably a group of society that can enrich their lives, by integrating possible solutions implemented considering the PWR. This interpretation opens the door to the development of future interfaces, which can be supported by an explicit way of measuring the well-being of someone inside a home.

INDEX TERMS Ambient assisted living, human-computer interaction, Internet of Things, smart homes.

I. INTRODUCTION

If predictions are correct, then, by 2022, there will be about 18 billion connected IoT-related devices [1] and some of these devices will certainly be used to monitor people at home (*e.g.* [2]), which is particularly important for older adults. It is a fact that overall life expectancy is increasing [3] and most families are not able to care for or spend enough time with their older adults. On the other hand, these (older adults) also prefer to live in their own homes, rather than living in nursing homes. Similarly, there are also several studies on the acceptance of adoption of Smart Home services by older adults and, although there are still several aspects that may not yet have a completely positive impact on their acceptance (*e.g.* security and privacy issues, the cost of establishing a smart house, electricity consumption and uninterrupted power availability), the acceptance perspective of these services is generally favorable [4]–[6].

For these reasons, Ambient Assisted Living (AAL) and Enhanced Living Environments are major areas, where efforts have been made in recent years, to address the quality of life of older adults. There is a vast literature in these areas, covering various fields of study (in [7]–[9] most research efforts and advances in these areas are presented). Likewise, there are also numerous larger projects and programs to improve the daily lives of older adults (including those co-financed by the European Union), such as: ALADIN (Ambient Lighting Assistance for an Ageing Population) [10]; CAALYX (Complete Ambient Assisting Living EXperiment) [11]; K4CARE (Knowledge-based HomeCare eServices for an ageing Europe) [12]; OLDES (Older People's e-services at home [13]; SHARE-IT (Supported human autonomy for recovery and enhancement of cognitive and motor abilities using information technologies [14]; SOPRANO (Service oriented programmable smart environments for older Europeans) [15].

Although several works exist in Ambient Assisted Living, Enhanced Living Environments, and also efforts to measure or quantify well-being, to the best of our knowledge, presently there is no universal formula that allows the quantification of the well-being of someone which may be parameterized according to each individual. Although generally well-being can be defined as the state of feeling healthy and happy, there are several dimensions in which well-being can be measured and undeniably the aspects of well-being are subjective [16] by nature.

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In the context of older adults, allowing for different persons to interpret a well-being rate in a universal, simple and comprehensive way, would represent an enormous benefit. This could bring several advantages, not only to the older adults, but also to the circle of persons that interact with them, either being doctors, nurses, caregivers, or family members.

The main research question of this work is "*is it possible to define a general metric to determine the level of well-being of older adults, which can be customized for each individual?*"

To answer this question, several other questions were raised which are answered in the following sections, namely: how can technology be used in the context of a smart home to obtain parameters associated with well-being? (section II); how to guarantee the availability and scalability of a system based on our proposal? (section II); which dimensions are responsible for the well-being of older adults? (section III); how can a simple and intuitive scale be defined that can be easily interpreted in the context of well-being? (section III); is it possible for a specialist to tailor the PWE? (section IV).

We streamline our approach by starting with a discussion on the well-being of older adults and the dimensions which can be used and then present how several approaches can be pursued to gather data on these dimensions. Then we present our approach, with the introduction of a Personal Well-being Equation to measure well-being, which is followed by a formative evaluation and discuss the major conclusions. Throughout this work, several specialists in different areas of health care for older adults were consulted.

The rest of the article is organized as follows. Section II describes the context in which the proposed measures for the well-being of older adults are introduced. The methodology for measuring the well-being of older adults is presented in section III, as well as the various dimensions considered. Several implementation possibilities are also presented for integration with the Personal Well-being Rating (PWR). Section IV presents a formative evaluation, carried out with experts, and demonstrates the results of applying the PWR with real examples, discussing the results obtained. Conclusion and the scope of future work are discussed in section VI.

II. WELL-BEING OF THE OLDER ADULTS

In this section, two different topics are discussed. The first is related to the context in which the measurement of well-being is carried out, in this case, in the context of smart homes for older adults, where much previous work has been carried out. The second topic focuses on previous efforts to measure well-being and on the classification of its associated dimensions.

A. WELL-BEING HOME

In previous work [17], we introduced a new model which may be perceived as an abstraction model (shown in Fig. 1), appropriate for the well-being of the older adults, for much of the existing smart home architectures and frameworks. The model is composed of three types of entities (agents, devices, and geography) and a Home Processing Unit (HPU). The latter centralizes all the information gathered from the household entities.

The HPU will also have the complex task of managing all these types of entities, in a smart home, to use them in an integrated manner and trigger appropriate actions when necessary (*e.g.* using emotion regulation through music and color/light, as in [18]). These actions will be supported by complex algorithms and will employ artificial intelligence techniques (as in other related literature, *e.g.* [19]–[21]) to communicate appropriate actions to household entities in a user-centered approach.

Fig. 1 shows the abstraction model for such a home. This can be integrated with eServices [22], a distributed architecture proposed in our previous work, as a support service platform for non-invasive continuous surveillance and social inclusion.

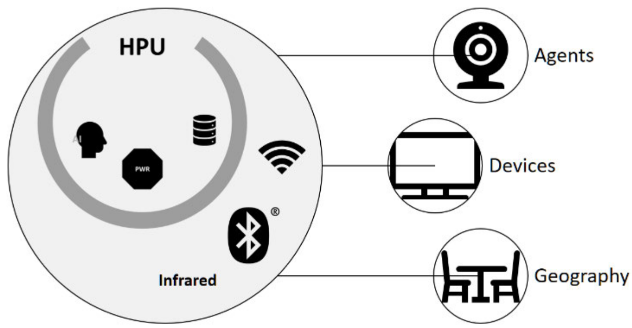

FIGURE 1. The model of a well-being home [17]. The HPU receives/sends data, through communication technologies, from/to the three types of entities: agents, devices, and geography. The PWR, based on the received data, calculates a value to be used by the HPU to trigger the appropriate events.

The advantage of integrating with this platform is to facilitate customer management and service integration. These eServices are linked to caregivers, health professionals, or family members and can alert them to any abnormal situations. They also communicate with the HPUs to see if they are connected. Depending on the degree of criticality, several solutions can be contemplated to ensure the availability of the system, although it increases the cost of the system. These solutions can be applied both in the eServices (*e.g.* through service redundancy, mirroring databases, among others), as well as inside the home, *e.g.* low-cost solutions, relying on a cheap and small cluster of HPUs per home (*e.g.* Raspberry PI computers) running a high-level integration platform (*e.g.* Node-RED to abstract sensors' communication protocols) and messaging brokers (*e.g.* RabbitMQ to route the acquired and already formatted sensor's data). These solutions may also include cloud management and monitoring systems to deal with high availability and automatic failback by using floating IP and multiple reverse proxies.

Fig. 2 shows the whole solution with this distributed architecture.

Indeed, in former work, we have demonstrated how to provide an AAL solution for older adults [23], which includes low-cost equipment and offers real-time communication

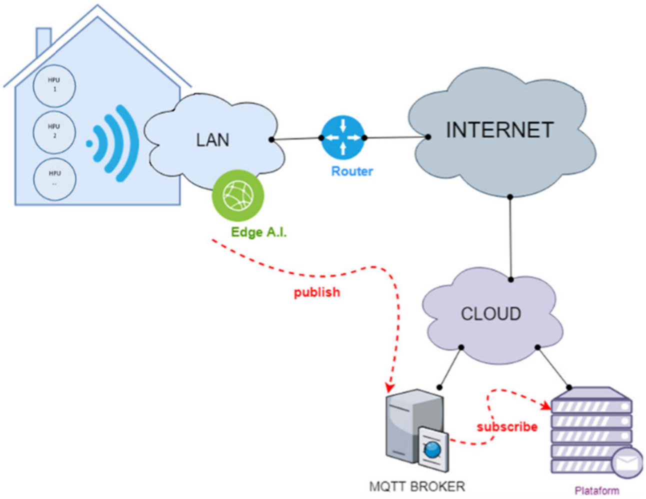

FIGURE 2. Distributed architecture with a well-being home integrated with the eServices which are linked to caregivers, health professionals, or family members.

with caregivers. The specific solution includes a system that is available anytime and anywhere, for family and caregivers. It uses low-cost devices to be affordable by anyone, applies machine learning algorithms, for the data being gathered by the IoT sensors, which allow the system to detect unusual behavior. Finally, it is adapted for older adults that live alone in their homes. The sensors are connected to resource-constrained IoT devices with communication capabilities (through an 802.11 network connected to an Internet provider) that are programmed to control and read values from sensors. The data is sent to a cloud-based platform, to be used in a supervised AI algorithm. The communication between devices uses the MQTT protocol, and an Edge Hub with the function of an MQTT broker, responsible for receiving and filtering messages, determining who is subscribed to each message, and sending the message to these subscribed clients. The LAN device sends MQTT to publish messages with information about data gathered in the home sensors, while the cloud platform receives MQTT subscribe messages. At the platform, a supervised mechanism is applied to all data received, to create patterns regarding the older adult's behavior, detect unusual actions and warn family and caregivers.

B. WELL-BEING MEASUREMENT

One of the challenges related to implementing an HPU is how to quantify the level of well-being of an older adult. The motivation of this article is the definition of a Personal Well-being Rating (PWR), which is constantly updated from the data collected from the entities of each of the dimensions. The details of how this PWR is determined is the motivation of section III, where a formula is proposed to deal with the dilemma of assessing the level of well-being of older adults.

The first question, when trying to define a formula for measuring well-being, is which aspects of the human being can influence the overall well-being of older adults. This is a subjective question, in which different authors may present different dimensions of well-being.

Indeed, measuring or attempting to quantify well-being has been addressed many years ago by many authors (*e.g.* [16], [24]–[29]) and covers several areas (including psychology, sociology, and health). In most cases the subject is treated from a psychological perspective, but sometimes it is also approached from other perspectives, such as spiritually (*e.g.* [29]) or even socially (*e.g.* [28]). However, what many authors agree on is that this is a subjective topic and there is no consensus on this matter. What we are trying to do with the expression of a well-being equation is to define a generic equation, which must be adapted individually, and can serve as the basis for further improvements.

However, some universal aspects undoubtedly contribute to the general well-being of human beings, such as: health conditions, physical activity, and emotional state. Thus, these three dimensions were chosen for the definition of a general formula of well-being centered on the user, as represented in Fig. 3.

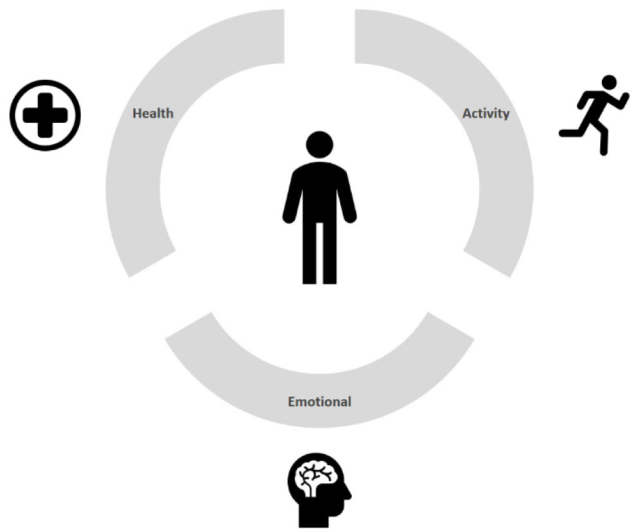

FIGURE 3. The three dimensions of well-being. All of these dimensions, health, activity, and emotional are user-centered and contribute significantly to a person's well-being.

Although different or more dimensions might have been chosen, we selected these because of the obvious contribution to one's well-being. It is clear to us that a person's well-being may depend on several other factors. However, these dimensions were chosen with two major concerns in mind: their main contribution to a person's well-being and because it is possible to use various types of sensors to collect data in each of these dimensions.

One interesting thing to note about these dimensions is that sometimes they are related. For example, a person may feel happy (emotional state) while watching a TV show (activity). Similarly, by monitoring a health condition (*e.g.* heart rate), this will certainly be affected by a more intense sports activity.

All of these dimensions are measured from data collected from the corresponding agents and devices to allow the HPU to calculate the PWR. This is calculated using the Personal Well-being Equation (PWE) introduced in section III.

One example of the need for classification, for one of the dimensions that we considered to be one of the bases for the definition of the PWE - health, is the International Classification of Functioning, Disability and Health (ICF) [30], [31] from the World Health Organization (WHO). The general purpose of this classification is to provide a unified and standardized language as well as a framework for the description of health and health-related states. Although this classification is mainly health-oriented, it also defines some health-related components of well-being.

There was no consensus among the various specialists consulted in the various dimensions related to the well-being of the older adults, but all acknowledged that the dimensions would always include health, activity, and emotional as basal for the well-being measurement. Until more investigation eventually allows us to gather a larger consensus for the definition of the dimensions of well-being, our effort has been to define a formula that is sufficiently generic to accommodate more dimensions as well as the possibility of disregarding some of the dimensions.

Similarly, the definition of quantification classes, scales, and words is a common practice used in ICF, where it is also indicated that evaluation procedures should be developed through research. It is also recognized in the ICF that for different users it may be appropriate and useful to add other types of information to the coding of each item.

Indeed, scales are common in several user-related areas, including Human-Computer Interaction (HCI), *e.g.* System Usability Scale (SUS), Post-Study System Usability Questionnaire (PSSUQ), Experience Percentile Rank Questionnaire (SUPR-Q), etc., and allow to measure multiple parameters, including self-reported behavior using rating-scale questions. However, these types of questionnaires are more directed to other types of applications and also vulnerable to response biases. In the case of older adults, it may be complicated to obtain reliable data with a questionnaire, even if these are supported in the answers with the help of professionals, derived from the subjectivity of classifying well-being. The existence of an automatic system to quantify an adult's well-being through a simple customizable equation thus becomes a key advantage for improving the living conditions of older adults who live in their own homes.

The use of equations to measure the user's response to a physical stimulus is not new. For example, in a distinct field, Alan Chalmers *et al.* proposed an equation of perception to measure how each channel of sensory input contributes to an overall perception experience of virtual reality. The proposed equation is a function of preconditioning and task [32].

The PWE has been thought of as a simple, meaningful, and effective way to give feedback on a person's well-being.

III. METHODOLOGY

Defining the dimensions of well-being is only part of the challenge. These dimensions are unlikely to influence everyone equally in the same way. For this reason, the Personal Well-being Equation includes a coefficient for each dimension

$$PWE(p) = K_h h + K_a a + K_e e, \tag{1}$$

where,

$$\begin{aligned} h &= health \\ a &= activity \\ e &= emotional \\ Kh &= health\ coefficient \\ Ka &= activity\ coefficient \\ Ke &= emotional\ coefficient \end{aligned}$$

plus,

$$K_h + K_a + K_e = 1$$

Each dimension is also provided as a value between 0 and 1 (100%), so an example of the formula application for an individual would be $PWE(individual) = 0.4_{(health)}\ x\ \ 0.9 + 0.3_{(activity)}\ x\ 1.0 + 0.3_{(emotional)}\ x\ 0.6$, which would result *0,84 (or 84%)*.

PWE is a function of a precondition (p). This is because the equation is determined based on an earlier condition for a particular person (which is why we have chosen to include the word "Personal" in the equation name). An older adult will not have the same health condition, will not perform the same activities, or have the same emotional reactions as a child, adolescent, or young adult.

The PWE also uses the word "Personal" because the definition of the weights to be used must be defined by specialists, who will evaluate each person and adapt the formula according to each specific case. Not only in the health dimension but also in the other dimensions, individual differences have to be adjusted (*e.g.* [33]–[35]). To simplify this multiplicity of values and allow their analysis, we opted for the use of scales, normalization of values, and words of quantification (similar to the practices used in the ICF [30] and the prescription of physical exercise, as the example of MET application by researchers, clinicians, and practitioners, among others, *e.g.* [36]). This allows for the values to be correctly interpreted by people from different fields and even to give proper feedback to the persons being monitored. Thus, in all dimensions, as well as in the final value, the bounding values are 0 and 100%. For the same reason, the sum of the coefficients should totalize 100%, with each coefficient representing the particular weight for the overall PWR.

It is expected that a person who has recently undergone a serious spinal injury will still experience a variety of inconveniences, including reduced muscle strength, fatigue, anxiety, and frustration. This will certainly limit the ability to perform various daily tasks and will be reflected in all dimensions of the formula. Thus, the suitability of the formula, during this recovery period, will often have to be assessed to reflect the evolution of the person.

Indeed, the WHO also recognizes the importance of full participation of people with disabilities and their organizations in reviewing a rating of functionality and disability. According to [31], in this context, the ICF will serve as the basis for disability assessment and measurement in many scientific, clinical, administrative, and social policy contexts.

The equation has three variables that can be monitored by agents from the dimensions shown in Fig. 1. Thus, the coefficients are individual but are expected to have some similarities between several people with similar characteristics (same age, same gender, etc.). These coefficients can be determined with the help of experts from related areas in the context of empirical studies.

Along with the coefficients, another concern is how to determine the value of each variable (h : *health;* a : *activity;* e : *emotional*). For this, we present some ideas based on previous knowledge and projects, including IoT projects. Table 1 shows examples of indicators to be used in each dimension, described later in the following sections.

TABLE 1. Dimensions and indicators.

Health	Activity	Emotion
pulse	type of activity	emotion expressed
heart rate	Metabolic Equivalent (MET)	duration
fall	time spent	intensity
…	…	…

There are several approaches (*e.g.* for determining the wellness of inhabitants using Wireless Sensor Networks (WSN) [37]–[39]) to collecting indicators for each dimension, but, regardless of the dimension, monitoring indicators should not interfere with the daily routines of older adults. For example, if we consider the health dimension, the monitored person will have a set of wireless body sensors to allow continuous monitoring of vital indicators. In previous work [40], we presented an architecture for smart homes, with several considerations on low cost, flexibility, and scalability, to record and analyze the daily routines of older adults. Fig. 4 shows a diagram of a fully integrated in-home automation and auxiliary system utilizing home automation technology to remotely and/or automatically monitor and control the state of installed electronic resources.

Indeed, much of previous work (*e.g.* [40]–[44]) is related to the development of assistive home systems, based on available technology, to ensure the quality of life, safety, and well-being of older adults where more specific implementation details can be found.

The following sections describe various strategies for assembling and measuring indicators for each dimension.

A. ACTIVITY

A measure that can be used to quantify the activity being performed is the Metabolic Equivalent (MET), which refers

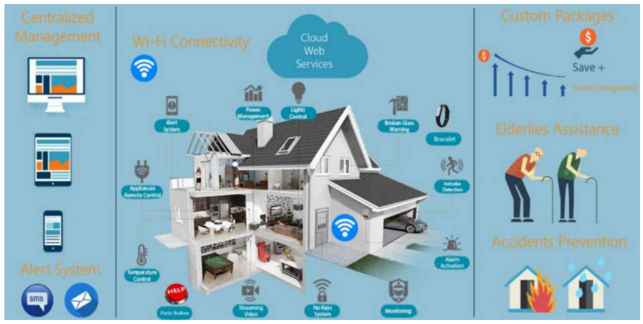

FIGURE 4. Full-integrated in-home automation and assistive system. The system was conceived with the main focus being low cost, flexibility, and scalability [40].

to the ratio between the metabolic rate of work and the Resting Metabolic Rate (RMR). MET is a physiological measure, used in the "Adult Compendium of Physical Activities" [45] of Ainsworth *et al.*, which expresses the energetic cost of physical activities.

MET values start at 0.95 (sleeping) and go up to 23 (running at 14 mph). In other words, this means that the Metabolic Equivalent ranges from 0.95 to 23 1 $kcal{\cdot}kg^{-1}{\cdot}h^{-1}$.

The "traditional" MET does not take into account individual differences (*e.g.* body size, body composition, age, and gender) and the RMR varies from person to person. Literature exists where the authors study the influence of individual differences (*e.g.* [33], [34]). For example, in the study presented in [34], the authors state that using measured or predicted RMR as a correction factor can appropriately adjust for individual differences when estimating the energy cost of moderate-intensity walking. In [35], Ainsworth *et al.* have also suggested that a correction factor may be required to adjust for individual differences when estimating the energy cost of physical activity.

In [34], the authors created a nomogram, based on maximal exercise capacity (METs) and age, for assessing a patient's ability to perform a dynamic exercise to quantify the level of physical disability or relative capacity for physical activity. The idea was to present norms for METs based on age, as well as population-specific nomograms, that enable physicians to assess patients' exercise capacity relative to their age group. Undeniably, there is a widespread application of the MET by researchers, clinicians, and practitioners to identify and prescribe physical activities as stated by the authors in [33]. Although, throughout this section, we present a general hypothesis to determine the daily METs, when accounting for individual differences the daily METs should be determined among specialists for each individual, as we also suggest in the other dimensions.

Considering a real example of an older adult day routine (woman, 59 years), Table 2 represents the list of activities performed and the total MET and minutes spent in each activity, totaling 1771 MET-min (minutes). Sleeping time (in this case 9 hours) is not considered in the examples. The

MET values were collected from the 2011 Compendium of Physical Activities in [45].

TABLE 2. Day-to-day activities of older adults.

Activity	MET	Minutes
cognitive activities (crosswords)	1.5	60
cooking or food preparation, cleaning	3.5	210
dressing, undressing	2.5	40
eating	1.5	80
leisure activities (embroidery, crochet and sew)	1.8	60
reading	1.3	30
showering, brushing teeth	2	45
sitting on toilet, eliminating while standing or squatting	1.8	30
sitting quietly and watching television	1.3	150
walking	2	120

The activities from Table 2 match recognized Activities of Daily Living (ADL) [46], [47]. More specifically, the table includes activities that correspond to basic ADL, *i.e.*, those that must be accomplished every day by everyone who wishes to thrive by their one (*e.g.* functional mobility: walking); and activities that match to instrumental ADL, *i.e.*, those not necessary for fundamental functioning, but still very important to give someone the ability to live independently (*e.g.* preparing meals).

The challenge lies in determining the activities performed by a person. IoT solutions can be used for this purpose, where sensors installed on some devices (*e.g.* television, stationary bike, etc.) can transmit information to the HPU. Another way is to use image processing algorithms and cameras to monitor activities (*e.g.* dance) that do not involve any kind of equipment.

Similarly, there are strategies for analyzing the daily behaviors of residents in the context of smart healthcare in smart home environments (*e.g.* [41], [42], [48]–[53]).

1) HUMAN ACTIVITY RECOGNITION

There is a lot of research in Human Activity Recognition (HAR) (*e.g.* [54]–[58]) and several reviews were made in the latest years (*e.g.* [59]–[65]), where several vision-based methods are used in many applications including video surveillance, health care, and human-computer interaction.

In the most recent of these surveys [65], the authors present a review of Human Activity Recognition, using video-based methods, especially for the activity representation (global representations, *e.g.* [58], [66]–[68]; local representations, *e.g.* [69], [70]; depth-based representations, *e.g.* [71], [72]) and classification methods (template-based methods, *e.g.* [73], [74]; discriminative models, *e.g.* [75], [76]; generative models, *e.g.* [77], [78]), where they divided human activities into a hierarchical structure with three levels also somewhat similar to what can be found in other surveys. These include: action primitives – the atomic actions at the limb level (*e.g.* raise the left arm); actions/activities (*e.g.* walking, running) and interactions – activities that involve two or more persons and objects (*e.g.* cooking, hugging).

The result of the research from the authors in [65] shows that HAR has achieved great success where methodologies and technologies have made tremendous development in the past decades and have kept developing up to date. Still, they recognize that several challenges still exist when facing realistic sceneries such as real-world systems or applications, where applying HAR approaches is still non-trivial. One of the reasons for this is the limited computing power which makes them hard to be implemented in real-time. One of the possible solutions in such cases is the use of inertial sensors to assist in the recognition of the activities. As imaging technology advances and computing devices, cameras and sensors evolve, novel approaches for HAR constantly emerge, which we believe will make this task easier.

Future work might even consider extensions to also allow monitoring of user activities outside their homes. Of course, in these scenarios, they should be considered as mobile agents that can track and monitor the user wherever he goes. This means that in the previous examples, the activity list could have a few more lines, such as Table 3, which raised the total MET-min to a new value of 2239 ($\sim$26.42% more).

TABLE 3. Additional activities.

Activity	MET	Minutes
playing with grandchildren	2.2	90
bathing grandchildren	2.0	30
walking with grandchildren to and from school	3.5	60

These additional activities refer to a hypothetical scenario in which older adults are responsible for bringing and receiving their grandchildren to and from school (assuming a pedestrian route, therefore walking), playing and bathing them - a reality known by many grandparents.

2) DAILY ROUTINES OF OLDER ADULTS

With the support of a direct-action member and coordinator of a physical activity program for the older adults, we performed a study that consisted of analyzing the daily routines of 10 older adults. The data was gathered from oral questionnaires performed to the older adults in their homes by the direct-action member (someone of their trust). All the participants reside in the small Portuguese city of Marinha Grande, a locality with around 10500 resident citizens and a population density of about 206.7 inhabitants per km^2 (population indicators by municipality, 2012 [79]). Their ages ranged between 59 and 80 years old, distributed by both genders (5 women and 5 men).

The activities from the daily routines were grouped in categories from the Compendium of Physical Activities [45]. Only the categories that were more relevant for the present study (those where significant MET are expended) were considered, namely: home activity (*e.g.* preparing meals, washing dishes, cleaning the house, ironing, etc.); Miscellaneous (*e.g.* reading, doing crossword puzzles, being with friends, etc.); occupation (*e.g.* embroidery, crochet, modeling, carpentry, etc.); self-care (*e.g.* eating, dressing, grooming, personal hygiene, etc.); walking. The activities, which are represented in the chart from Fig. 5, do not include time spent sleeping (night/naps), which averaged about 9 hours per person.

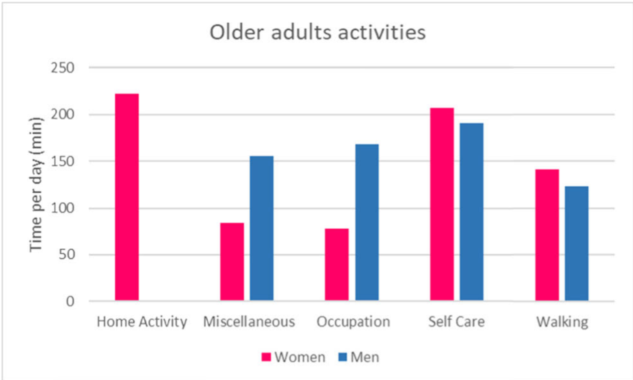

FIGURE 5. Minutes per day spent in each category of activities by 10 older adults of Marinha Grande, Portugal. In the category "Home Activity" none of the men registered any time of activity (associated with home chores).

As can be seen from the graphic of Fig. 5, there is still a big difference in the activities carried out by the different genders. None of the men performed the traditional domestic chores (*e.g.* preparing meals, washing dishes, cleaning the house, etc.). However, these spend more time than the women developing other leisure activities (*e.g.* modeling, carpentry). Conversely, it was observed that the women spent more time self-caring and walking. It should also be noted that the average age for women and men was approximately the same (women: 66.8; men: 68).

The graph in Fig. 6 represents the average MET-min (minutes) per day spent in all the activities categories, considered in Fig. 5, for both genders. It does not include time spent sleeping (night/naps), which is approximately 9 hours on average.

On average the older adults represented in this study achieved about 1908.6 MET-min (standard deviation of about 322.29), with women slightly above this number as shown by the graph (women: ∼2133; men: ∼1683).

3) RECOMMENDED DAILY ACTIVITY

We are confident that healthier, more active, and satisfying lifestyles are possible through solutions that efficiently use MET measurements. However, to have significant values for this dimension, a scale is needed.

One possible way to achieve this is to consider Recommended Daily Activities (RDA). To establish meaningful RDA, we analyzed several recommendations on physical activity for healthy lives and specific concerns or recommendations regarding older adults.

One example is the Global Recommendations on Physical Activity for Health for 65 years and above [80], from the World Health Organization (WHO). In these recommendations, we identified several activities identical to those performed by the older adults from our study, including

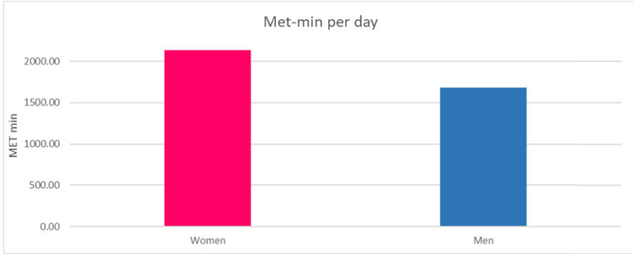

FIGURE 6. MET-min per day for both genders. Women: ∼2133; men: ∼1683.

leisure time, physical activity, transportation (*e.g.* walking or cycling), occupational, household chores, play, games, sports, or planned exercise. Although we have some participants with ages slightly less than 65 years, we can observe that, also in the recommendations from the WHO, in the 18-64 years range [81] some of the proposed activities are identical.

Another example is the one in [82], from the World Confederation for Physical Therapy, which presents recommendations that refer to the same activities presented by the WHO and also uses the Metabolic Equivalent (MET) for the respective values.

Also, in the Pacific Physical Activity Guidelines for Adults, from WHO [83] physical activity is addressed using the MET where, "*according to the Global Physical Activity Questionnaire (GPAQ) scoring protocol, physical inactivity is defined as a score below 600 MET-minutes/week, moderate-intensity physical activity is assigned a score of 600-1500 MET-minutes/week, and vigorous-intensity physical activity a score of more than 1500 MET-minutes/week.*" [83]. Moreover, in these guidelines is stated that "*an activity assigned 3-6 METS is considered moderate intensity and an activity of >6 METS is considered vigorous-intensity physical activity*" [83].

In another source, namely in the "Physical Activity and Public Health in Older Adults: Recommendation From the American College of Sports Medicine and the American Heart Association" [84] the differences between the older adult and adult recommendations are discriminated and also the MET is used. In the Physical Activity Guidelines from the Office of Disease Prevention and Health Promotion (ODPHP), which is part of the U.S. Department of Health and Human Services [85], it is stated that "*Some adults have low levels of fitness, particularly older adults. For these adults, activities in the range of 3.0 to 5.9 METs are either relatively vigorous, or physiologically impossible.*" [85].

Our motivations for reaching the RDA values are based on the several recommendations and insights that we have gathered from all these sources and on the analysis from the daily routines of the older adults from our study.

In the first step, we have decided which of the activity categories to consider. The graph from Fig. 7 represents the MET-min week for each category.

From the categories in Fig. 7 (gathered from our study with the older adults from Marinha Grande, Portugal) we chose the activity categories from the Compendium of Phys-

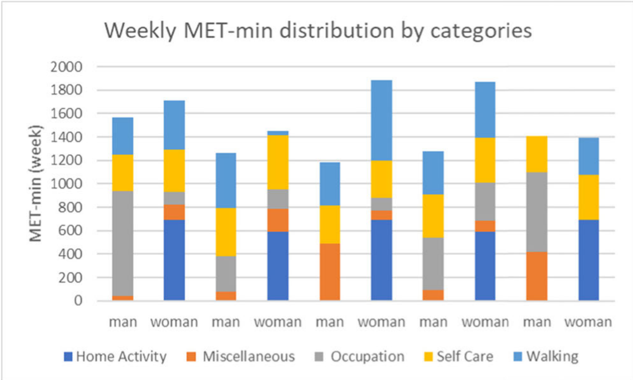

FIGURE 7. MET-min per week spent in each category for both genders.

ical Activities that match the recommendations from the WHO guidelines, namely ''home activity'', ''occupation'' and ''walking''.

The second step consisted of determining the RDA. For this we followed the WHO guidelines where physical inactivity is defined as a score below 600 MET-min/week, moderate-intensity physical activity 600-1500 MET-min/week, and vigorous-intensity physical activity more than 1500 MET-min/week. Hence, we considered these scores as threshold goals to determine a classification that may be simply understood. Table 4 shows the correspondence between the MET-min/week thresholds and the corresponding classification.

TABLE 4. MET-Min/week and classification.

MET-min/week	Classification
<600	insufficient
600-1500	sufficient
>1500	good

However, the goal of the PWR is to monitor the daily activity (whereas the guidelines are in MET-min/week). To simplify the succeeding analysis, we converted the Met-min/day from our study to MET-min/week by multiplying them by the number of days in a week (not considering weekends). The foundation for that is that we want to be able to provide daily feedback. Moreover, from our contact with the older adults from the study, their days are made of routines that pretty much are equally from day to day. The changes occur mostly on weekends, where most admit spending more time resting. This was also confirmed by the several professionals in healthcare that we consulted. Nevertheless, in the future, there is the possibility to also consider weekly, monthly, or any other period feedback.

By only considering the three categories specified (home activity, occupation, and walking) we can observe in the graph from Fig. 8 that all the older adults would be rated good in this dimension. This makes sense since all of them are still very active persons: almost walk a lot daily (either by simply leisure or going to the coffee and/or by go take/pick up grandchildren to/from schools), have daily occupations, and in the case of women perform several home chores (such as cooking, cleaning, ironing, etc.).

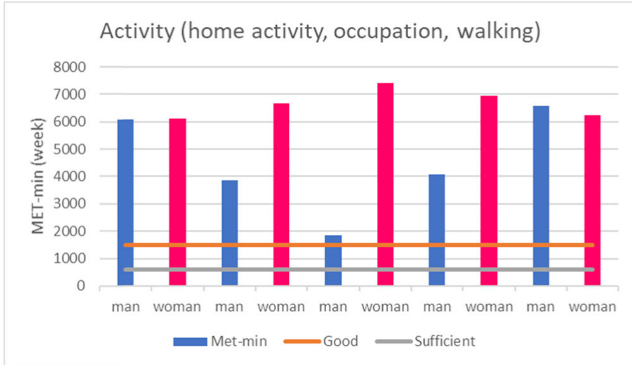

FIGURE 8. MET-min per week for both genders. The thick orange line (upper horizontal line) is at 1500 MET-min/week – values above the line are considered good. The thick grey line (lower horizontal line) is at 600 MET-min – values below the line are considered insufficient. Values between the two thick horizontal lines are considered sufficient.

Due to the home activity, performed only by women in the present case study, women have significantly higher MET-min/week values than men. The influence of the daily chores, performed by women, in the MET-min/week, is evident in the graph from Fig. 9, where the home activity was not considered lowering their MET-min significantly.

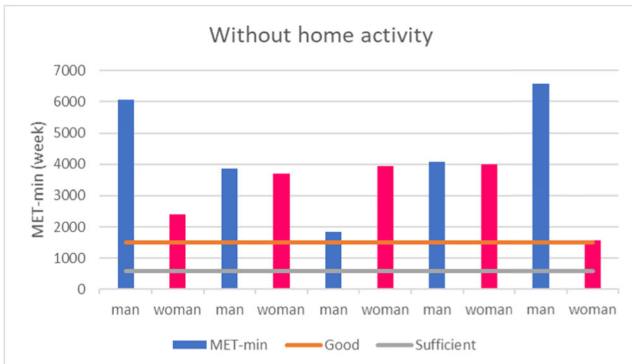

FIGURE 9. MET-min per week, considering only occupation and walking, for both genders. The thick orange line (upper horizontal line) is at 1500 MET-min/week – values above the line are considered good. The thick grey line (lower horizontal line) is at 600 MET-min – values below the line are considered insufficient. Values between the two thick horizontal lines are considered sufficient.

In Fig. 10 and Fig. 11 we may observe, respectively, the MET-min/week if the participants had no occupation or didn't walk daily. Almost all of the older adults performed daily activities in both categories. All walked several minutes daily and only one man and one woman had no occupation.

In the graph from Fig. 10, we can see that the activity from one man was rated sufficient. All the other participants had their activity rated good.

Also, in the graph from Fig. 11, the activity from one man was rated sufficient and the activity, from another man, rated

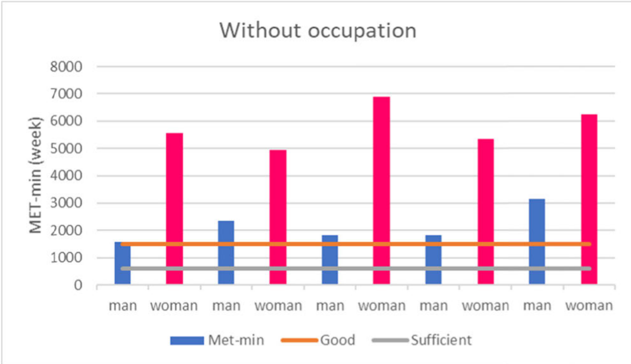

FIGURE 10. MET-min per week, without considering occupation, for both genders. The thick orange line (upper horizontal line) is at 1500 MET-min/week – values above the line are considered good. The thick grey line (lower horizontal line) is at 600 MET-min – values below the line are considered insufficient. Values between the two thick horizontal lines are considered sufficient.

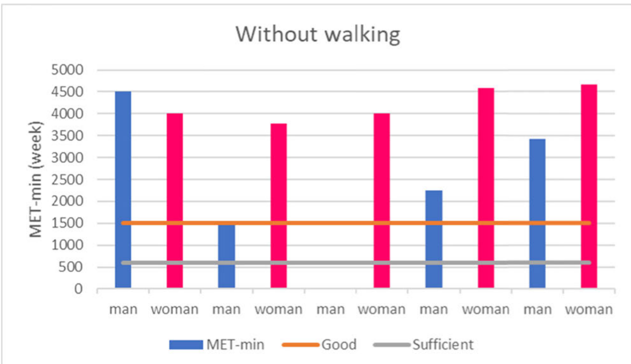

FIGURE 11. MET-min per week, without considering walking, for both genders. The thick orange line (upper horizontal line) is at 1500 MET-min/week – values above the line are considered good. The thick grey line (lower horizontal line) is at 600 MET-min – values below the line are considered insufficient. Values between the two thick horizontal lines are considered sufficient.

insufficient since it didn't perform any home activity and had no occupation (the reason why there is no bar in one of the participants). All the other participants had their activity rated good.

Still, removing only one of the categories identified in Fig. 10 and Fig. 11 is strongly attenuated by the other category, since almost all of the older adults performed daily activities in both categories.

The third step consisted of determining a Maximum Daily Activity (MDA) as a value above the one it is considered that the gains in health are not significant. Therefore, it will be the limit for our scale and any eventual value above it will be rated as the maximum value in this dimension (100%). To reach a meaningful value we considered the recommendations from the World Confederation for Physical Therapy, in [82] which states that "*most health gains occur when people achieve 3000 to 4000 MET minutes per week*" [82], but where these are not specific to older adults. Taking into consideration the specific case of older adults, the data collected from the participants in our study, and all the other recommendations already presented, we have decided to define the value 3000 as a weekly MDA. Since we want a daily value (instead of a weekly), for the reasons already addressed in this section, we divide the value 3000 by the number of days in a week to reach the final, rounded, MDA of 429.

However, we do reason that the values should be established amongst specialists and case-by-case (which are also the recommendations from several of the health-related organizations). For these studies, experts in several areas can be involved, automatic techniques used (*e.g.* [37]–[39]) and tools such as the Physical Activity Scale for the Elderly (PASE) [86], a questionnaire that examines self-reported occupational, household, and leisure activities.

In a final step, and to standardize the final activity rating, we have decided to normalize the value to a range of 0-100%, using a simple rule of three, for each range of the recommended daily activity values,

$$activity = RDA\ range^{*}100/MDA \tag{2}$$

after this, the corresponding classification from table 4 translates to the classification presented in Table 5.

TABLE 5. Activity rating.

Rating
good > 50%
20% ≤ sufficient ≤ 50%
insufficient < 20%

So, it's all about the Recommend Daily Activities (RDA) and Maximum Daily Activity (MDA) value to be used and more research in this field can still be held to improve them. Similarly, within this approach, more empirical studies can be carried out. These values can also be customized, *i.e.* adapted to each user to improve classification efficiency.

B. EMOTIONAL

In HCI, human emotions have also been widely discussed, following different strategies or computational models for the regulation of affection or emotion (*e.g.* [18], [87]–[95]). There are also several fields where these have been studied (*e.g.* sports [96], virtual storytelling [97], games [98], therapeutic fields [99]). The detection of human emotions in homes is also being addressed recently and, focusing on a more directly related field, the older adults [39], [40], [100]–[103].

Emotions are therefore essential for human interaction, where emotional expressions are constantly monitored and interpreted. The question that arises is: which emotions should be identified? This is not a recent issue if we consider that the study of emotions can be reported at various times. In the ancient Greek treatise on the art of persuasion "Aristotle's Rhetoric" [104], dating from the 4th century BC, through "The Expression of Emotions in Man and Animals" by Charles Darwin in 1872 [105] and the eight basic emotions of Robert Plutchik's theory in 1980 [106].

The emotion we consider most important in our study is happiness. Other emotions are also significant and very interesting to analyze additional issues (*e.g.* occurrences of fear may alert us to something that may be wrong with a person - if the person is not watching a horror movie). However, in this study, we are only interested in the overall happiness of a person, to measure the emotional state. Sadness can also be considered, but it has some disadvantages. For example, it can last much longer than other feelings (sadness can last, on average, for 120 hours [107]). It is easy to understand this duration if we imagine some events, such as a divorce or the death of a loved one. Yet, even in times of sadness, it is possible to have some happy feelings (*e.g.* seeing a grandchild learning to walk). For these reasons, we decided to focus first on happiness.

Since smiles are associated with happy feelings, these can be used to identify this emotion. However, no one has a smile on his face all the time. Therefore, alternative approaches could be considered, and one is to count the number of smiles per day. Smile detection is a common feature of various devices, such as modern cameras and smartphones that can take pictures automatically, triggered by smiles. There are also countless ways to detect smiles (*e.g.* [108]–[112]).

The challenge behind an approach based on counting smiles is how to determine how many times a day it is normal for a person to smile. Several aspects influence this measure, for example, the country of origin and the age of a person. There is a study that says a UK adult smiles 11 times a day [113]. It is also well known that, in general, children smile much more than adults. According to the study in [113], it is also reported by a psychologist that "*It's interesting to see that the majority of people think that they should smile at least seven times a day in order to feel happy and content.*" and that "*smiling has a huge amount of real value—recognised by more than 90 per cent of us—and, when the number of times you smile every day is added up, it can have great benefits to overall happiness.*" [113].

The simplest emotional measurement approach would then be to count the daily number of smiles for a person and then rate it appropriately.

One thing that can be considered is whether a person should know that she/he is being evaluated through smiles (in this dimension) since she/he might be tempted to make false smiles. In an ideal system, however, these would be recognized as false and therefore disregarded. Indeed, there are several ways to automatically distinguish between true and false emotions. One instrument for this is the Facial Action Coding System (FACS) [114], a system that allows the characterization of physical expressions of emotions, presented in more detail later in this section.

Literature can be found based on this system (and using the facial Action Units), and also referencing the vast work of Paul Ekman *et al.* to taxonomize human facial movements by their appearance on the face (*e.g.* [114]–[118]). Numerous examples of approaches to distinguish between true and fake smiles can be found (*e.g.* [119]–[124]) where the authors achieved very convincing results. For example, in [121] the authors, using image-based methods, analyzed the muscles associated with smiles, defining Regions of Interest (RoI) such as the mouth (which can be identified by the appearance of wrinkles at the corners of the cheeks) and the eyes (which can be identified by the elongation of the eyes). The use of RoI that includes more than the mouth is frequent in most approaches, to improve the accuracy when distinguishing between real and fake smiles.

In the presented example, results show an accuracy of the system of 86% with an error rate of 14%. This value is similar to the one from the authors in [119] and higher than human true *vs.* fake smile recognition ability as stated in [119].

What allows to differentiate a real smile from a fake one is the muscles that are contracted. Both real and fake smiles are characterized by the contraction of *zygomatic major* muscle (on the edge of the mouth corner). However, in a real smile the *obicularis oculli* muscle contracts whereas in a fake it doesn't. The authors in [120] also state that "*Reliable expressions are expressions said by the psychology community to be impossible for a significant percentage of the population to convincingly simulate, without feeling a true inner felt emotion*" [120].

Studies also exist related to Human–Robot Interaction (HRI) focusing on smile recognition to recognize a human's mood while interacting with robots, such as in [125].

Still, happiness is not easy to measure, if we consider that it can also be composed of several separable variables. In [25], the authors describe as related variables: positive feelings, negative feelings, and satisfaction with life.

Considering the challenges expressed, concerning an approach to quantify happiness based on smile counting, and considering that there are not enough scientific studies—that we are aware of—that can provide us enough evidence, to determine a scale in which we can classify the number of smiles, we concluded that alternative approaches should be considered.

Indeed, there are more ways to detect happiness as well as other emotions. For example, in [126] wearable devices based on electrodermal activity are used by Zangóniz *et al.* to detect calm/distress conditions. Colour analysis of facial skin can also be used (*e.g.* [127]) and even vocalizations (*e.g.* laughers) can also be used to detect emotions, as in [128], [129]. Color/light and music can even be used for emotion regulation (*e.g.* [18]).

Similarly, well-being can also be explicitly asked of a person by asking questions and measuring scales exist, *e.g.* for example, the Warwick-Edinburgh (WEMWBS) Mental Well-Being Scale [130].

As stated earlier in this section, the FACS can be used to detect emotions and has been used by many authors effectively (*e.g.* [114]–[118]). This system encodes individual facial muscle movements and has been used by physiologists

TABLE 6. FACS emotions.

Emotions
happiness
sadness
surprise
fear
anger
disgust
contempt

TABLE 7. Emotional rating.

Rate	From	To
Good	Gmin	Gmax
Sufficient	Smin	Smax
Insufficient	Imin	Imax

and animators. It has also been established as an automated system that extracts the geometric features of faces in videos and produces temporal profiles of each facial movement. More recently it has also been used in real-time 3D automatic recognition technology [131]. The FACS also defines Action Units (AU), which represent the contraction or relaxation of one or more muscles.

The FACS represents several emotions (represented in Table 6).

Another issue in the way the measurement is performed is to also consider the intensity of the emotion. According to the FACS, the emotions can be expressed in different intensities, represented in Table 8. Several FACS intensities are identified, ranging from "trace" (the minimum intensity) to the maximum intensity ("maximum").

Some studies relate the intensity of the emotions to the prediction of some things, such as: future happiness [132], [133], stability in marriage [134], and longevity [135]. There is also some controversy about how to estimate the intensity of expression [136]. Therefore, it is not clear to us the influence of the intensity of an expression on happiness, *i.e.* the influence on happiness between expressed in its maximum intensity and expressed only as a trace.

Indeed, there is a vast literature concerning the detection of emotions through facial expressions or even distinguish between spontaneous posed facial behavior (*e.g.* [137], [138], [139]–[153]) and many different techniques may be used to detect emotions, and more specifically, happiness. The question that follows is: how to measure the emotional factor?

The idea is still to provide a simple classification that indicates the emotional rating as good, sufficient, or insufficient. However, the values to be used in this classification will depend on the approach pursued. For example, let's consider that the approach will measure the amount of daily time a person is happy. Even so, these values should be determined by specialists, similar as in the previous dimension, and for each case. Each person has her/his only personality which con-

TABLE 8. Intensity of emotions.

Intensity of Emotions
trace
slight
marked or pronounced
severe or extreme
maximum

figures a specific mood, characterized by different emotional states, as confirmed by our specialists. Hence, we emphasize the significance of defining our equation as a function of a precondition as we did.

According to these premises, and following the example of the activity dimension, we divide the rate of this dimension into three possible classifications according to limits defined for each person: insufficient, sufficient, and good (represented in Table 7).

Future studies could also consider analyzing more emotions and addressing the specific limits for a specified approach with psychologists. There are several detection/recognition models/methods on affect which can be used (some report accuracies above 90%) and several surveys comparing them exist (*e.g.* [154], [155]).

C. HEALTH

Health is certainly a dimension of major importance to the quality of life of older adults, but it is sometimes also the easiest to monitor (depending on the type of health indicators we want to analyze). It is in this dimension that there is also a vast amount of previous work (*e.g.* [43], [51], [156]–[163]) and several monitoring systems are commonly used, such as: pulse, blood pressure, heart rate, fall detection devices, and panic buttons. Most of these devices are wearables that monitor, in real-time, the health status of humans. These devices must have versatile functions and be user-friendly (to enable older adults to perform tasks with less intrusion and disturbance, pain, inconvenience, or movement restrictions [40]).

There are several examples of devices and solutions related to this dimension. In [100], the authors present an Android-based smartphone with a 3-axis accelerometer, used to detect their carrier falls, in the context of an intelligent home monitoring system. In [39], Gaddam *et al.* describe intelligent sensors, with the cognitive ability to implement a home monitoring system, that can detect abnormal patterns in the daily household activities of older adults. Based on electrodermal activity, wearable devices are used by Zangóniz *et al.* in [126], to detect calm/distress conditions. Cameras can also be used as fall detection systems for older adults, as in [164]. Even wireless acoustic sensors are considered, for ambient assisted living systems, for personal health care, as in [165].

Regardless of the approach taken, as well as the two dimensions already presented (activity and emotional), this dimension must also be quantified as a value that is meaningful and can be used. In a sense, we can use the same rating type used in the other dimensions, and that is our goal. However, delicate apprehensions with the health dimension bring some additional concerns, when it is considered a way of quantifying a person's health state. At the beginning of this section, we say that it is relatively easy to monitor some health indicators, but the same does not apply when we want to translate all this information into a single value.

A hypothesis to address the quantification of the health dimension considers the same principles used in the definition of the Personal Well-being Equation: defining a health equation that is a function of a precondition (p) and considering coefficients (determined among specialists) for the different sub-dimensions (*e.g.* pulse, blood pressure, heart rate) to be measured.

Again, the coefficients are individual but are expected to have some similarities between several people with similar characteristics (same age, same gender, etc.). It is wise to define these coefficients among specialists in the medical field, such as doctors, nurses, and even caregivers. They will therefore be consulted before venturing to propose a formula based on a dimension as important as health.

D. PERSONAL WELL-BEING RATING

Now that we have determined how to collect information and assign a meaningful rate to each dimension, it is time to put it all together.

As mentioned at the beginning of section III, each dimension contributes according to a certain weight which may vary according to the user's preconditioning.

The rating can be represented as a cylinder composed of three dimensions, each contributing to the final punctuation given to the user, as in Fig. 12. In this figure, it is easy to observe and compare the dimensions. In the cylinder, the user reaches the maximum in the activity dimension (100% - being rated good), slightly smaller in the health dimension (90% - also being rated good), and even smaller in the emotional dimension (60% being rated sufficient).

The figure also includes a smiley-based assessment, where each type of face corresponds to each rate so that a happy face corresponds to good, a neutral face sufficient and a sad face to insufficient (as in Table 9).

This pictorial system can be understood as an alternative to the textual category, but with some advantages, particularly useful in the case of older adults. It is a fact that, over time, our sensory capacities diminish, such as hearing and vision (sometimes also affected by some diseases, such as cataracts). In some cases, the mental state may also be affected and there are also some cases of illiteracy. This may complicate the interpretation of some interfaces. User interfaces based on detailed textual elements and metrics (numbers, proportions, and percentages) are therefore not recommended if we want to provide information to those users. However, additional scenarios may exist, where information is transmitted only to a caregiver or family member.

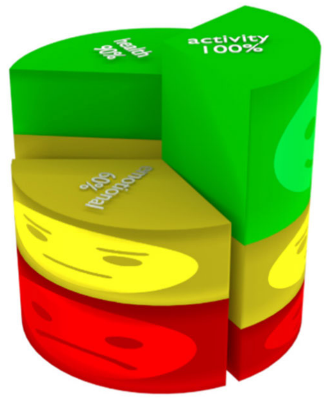

FIGURE 12. Cylindrical representation of the three dimensions. The cylinder is "sliced" in the three dimensions considered for well-being. The height of each "slice" is assigned by the value of each dimension and represented by the corresponding smiley. Note the different heights of each classification in the activity dimension, due to each of the recommended daily activities.

TABLE 9. Smiley rating.

Rate	Smiley
good	
sufficient	
insufficient	

The use of smiles is a more universal scale, which can be easily interpreted from the data collected by the user. Smiley faces also make use of a color scheme, where the sad face is red, the neutral yellow, and the happy is green. Although these colors alone have semantic interpretations in our daily lives, color is only used as a complementary medium because of the issues already raised (*e.g.* sensory and cognitive impairments) and because there are also a significant number of color-blind persons. This duplicity conveys some flexibility in the use of possible implementation solutions, since caregivers, for example, have two different ways of asking someone for their visual Personal Well-being Rating (by the smiley face and by the color).

This does not mean that more specific information should be disregarded. Different levels of access can be defined. For a doctor, evaluation through smiley faces will certainly not be adequate. Instead, it may be more important to observe the vital signs collected over some time. This is not, however, the topic of the present study. For this study and many of the concerns presented in this article, the approach to smiley faces may be helpful.

Evaluation through smiley faces is often used from a young age. Primary school teachers use it to get feedback from children in school activities or to provide behavioral information to parents (as in Fig. 13). These scales are not only used in the field of education. They are also used, for example, in the context of health (*e.g.* to measure pain [166] or to determine dental anxiety among children [167]).

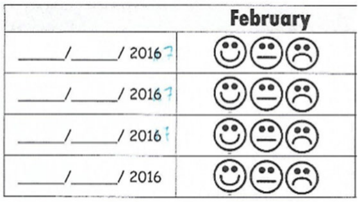

FIGURE 13. Children's behavior information form to parents from an elementary school.

Likewise, these scales are not limited only to children. It is common to see smiley faces in various places being used among adults. An example is to evaluate customer satisfaction in retail stores and public services or even traffic information, as in Fig. 14 to indicate if the speed limit has been exceeded. This is a fun and simple way to receive and/or transmit information.

FIGURE 14. Smiley faces being used in traffic information.

The same system of smileys is the one that will be used in the final rating. Due to the normalization of the corresponding dimensions and weights, the Personal Well-being Equation (PWE) will return a value between 0 and 1 (which can be interpreted as 0–100%) and the same scale can be used for the final PWR (given by the PWE).

Given the example shown in Fig. 12, and considering some subsequent arbitrary values and coefficients (for hypothetical preconditioning of the imaginary person we called Ann), the corresponding PWR would be determined by

$$PWE(Ann) = 0.4_{(health)}\ x\ 0.9 + 0.3_{(activity)}\ x\ 1.0 + 0.3_{(emotional)}\ x\ 0.6 \qquad (3)$$

which means that on our scale it will get a PWR of 0.84, so it would be rated good with a happy face.

One thing to note about this PWR is that it is assumed that a person is not in any type of critical condition, *i.e.* it is not intended to be used in an emergency device. In Ann's PWR, even if she had a severely affected health and the corresponding value rated "0", she would still have a PWR of 0.48 (it would be considered sufficient, which would not be appropriate - imagine if the "0" in the health resulted from the heart suddenly stop beating). Some modifications can indeed be made to deal with such situations, but this is not our goal. In our view, critical states should be treated by a more specific and robust system. The PWR is intended for monitoring a person's overall well-being, not as a mechanism for dealing with critical conditions (therefore, it should not be used to replace other types of systems such as panic buttons, emergency alarms, or similar systems).

In the Personal Well-being Equation, if we consider that, for a certain precondition, one or more factors should not be used, we can simply assign them the coefficient corresponding to a value of "0". The equation is thus easily adequate for each case. For example, it may not make much sense to give a large value in the activity coefficient for someone who has serious mobility problems, which prevent her/him from performing various tasks.

IV. EVALUATION, RESULTS, AND DISCUSSION

Although this is the first step in defining the PWE, it was presented to several professionals in healthcare. We followed a formative evaluation by conducting seven interviews. The interviewees are:

- CEO of a company in healthcare;
- Occupational therapist;
- A technical director and psychologist of a nursing home;
- A doctor;
- A nurse;
- A direct-action member and coordinator of a physical activity program for the older adults;
- A professor at a senior health science school specializing in people in their final stages of life.

All of these participants work with older adults in their professional activities. The main objective of the interviews was to determine whether they considered the dimensions of the equation appropriate and whether it was possible to define appropriate weights for each dimension.

When asked if they consider the dimensions appropriate, they all recognize the intrinsic value of health, emotions, and activity for the overall well-being of older adults. The occupational therapist cited "psychological" and "social" as possible additional dimensions, the nurse also included "social". Both these dimensions are also found in other literature [168]. The professor of health sciences included "psychological," "emotional," and "spiritual", but as sub-dimensions of health. Although some different dimensions have also been considered, all participants recognize that they "fit" into the dimensions already proposed. It has also been mentioned that some dimensions are related, *e.g.* it is difficult to feel good (emotional) when facing serious health problems. Taking all these assumptions into account, we believe that the dimensions are appropriate, but also additional dimensions can be added to the equation.

Regarding the weights (coefficients) of each dimension, it was agreed that these should be defined individually, as there are strong differences among the older adults. This fact confirms the need to have an equation for each individual, with weights adjusted accordingly. It was with this premise that we decided to define the equation as a function of a precondition. These coefficients must therefore be adjusted in an initial parameterization process to ensure that the equation returns significant values. This can be done, by experts, the first time an equation-based system is used and adjusted periodically to ensure proper use of the equation.

Another aspect in which all participants agreed was the possible use of interfaces based on smiley faces.

To determine the daily activities, we consulted the direct-action and coordinator of physical activity for older adults to obtain a list based on the daily life of two older adults. Table 10 corresponds to a woman of 59 years and Table 11 corresponds to a man of 65 years. Both are retired and live in their own homes.

TABLE 10. Activities of a woman, age 59 years.

Activity	MET	Minutes
personal hygiene: washing teeth	2	5
personal hygiene: bathing	2	40
dressing/undressing	2.5	40
walking	3.5	90
go to the cafe (walking)	3.5	30
meals (breakfast, lunch, snack, dinner)	1.5	80
leisure activities (embroidering, crochet and sewing)	1.8	60
domestic activities (ironing, cleaning the house, preparing meals)	3.3	210
reading	1.3	30
watching TV (after nap and dinner)	1.3	150
cognitive activities (crosswords)	1.5	60
going to the bathroom	1.8	20

TABLE 11. Activities of a man, Age 65 years.

Activity	MET	Minutes
personal hygiene: washing teeth	2	5
personal hygiene: bathing	2	25
dressing/undressing	2.5	30
walking	3.5	60
go to the cafe (walking)	3.5	30
meals (breakfast, lunch, snack, dinner)	1.5	80
leisure activities (modeling)	2.5	360
reading	1.3	30
watching TV (after nap and dinner)	1.3	150
going to the bathroom	1.8	40

The purpose here is to demonstrate how each dimension can be used and the formula tailored for each user. The example considers only the activity dimension, but this also allows us to show the flexibility of the equation since it is not only possible to add more dimensions (just add a new variable and the corresponding coefficient), but also to exclude others. For this reason, considering that we only want to measure the activity, we define the coefficients of the other two dimensions as "0" (PWE (p) $= 0$ h $+ 1$ a $+ 0$ e).

Considering the reference RDA (Recommended Daily Activities) labeled in section III and excluding sleeping time, both the older adults would receive a PWR of 100%, rated good, which, looking at the level of activity they perform, makes sense. However, for example, if the man did not walk, he would have a PWR of $\sim$49.97 (sufficient).

The effect of simultaneity has not yet been considered in this study. Some dimensions indeed influence others, which does not mean that they can be individually measured. However, the question related to simultaneity exists. Imagine the hypothesis in which a person does not feel well physically (health) but that she is developing an activity that typically makes her smile and feels good emotionally. However, she smiles, for this reason, fewer times and thus negatively affect the emotional dimension as well. Considering a sufficiently intelligent system, the equation's weights could automatically be adapted to contemplate this situation, based on the specialists' knowledge. It is assumed, however, that it is underlying that in some of the methods presented they are not yet fully universal, that is, there are clinical conditions in which it may not be possible to determine the correct value of some dimensions. To improve this the development of technology is essential and there have been several recent developments in different types of interfaces and interaction methods (*e.g.* Brain-Computer Interfaces) that could lead to the universalization of the PWR.

V. CONCLUSION AND SCOPE OF FUTURE WORK

Reality shows us that there is a growing number of older adults living alone in their homes. In recent years much research has been performed to develop various architectures, frameworks, and devices to collect information. This information allows us to determine the condition of the older adult population in their homes and act in some way to improve their lives. We believe that the Personal Well-being Equation introduced in this article is a valuable step towards the definition of a general equation, which can be parameterized to determine the well-being of older adults. It was presented in all dimensions considered, with some examples demonstrating which values are expected from the application of the equation.

The equation, however, was not defined to consider the effects of simultaneity. Each of the variables is interpreted individually. Several other variables may even be included, and future improvements can be thought of. This is therefore a field of study that is certainly of significant interest to us, in the near future. In future work, we also intend to study the use of other types of scales for each dimension.

These future improvements in the equation will serve as the basis for the development of several user-centered devices, that will use different means, including smiley-based representations, to provide useful feedback on the well-being of older adults, and hopefully be part of more satisfying aging.

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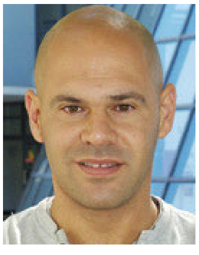

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