

An Unobtrusive System to Monitor Physical Functioning of the Older Adults: Results of a Pilot Study

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Abstract. The Aging phenomenon entails increased costs to health care systems worldwide. Prevention and self-management of age-related conditions receive high priority in public health research. Multidimensionality of impairments should be considered when designing interventions targeting the older population. Detection of slow or fast changes in daily functioning can enable interventions that counteract the decline, e.g. through behavior change support. Technology facilitates unobtrusive monitoring of daily living, allowing continuous and real-time assessment of the health status. Sensing outdoors remains a challenge especially for non physiological parameters. In this paper we present the results of a pilot study on monitoring physical functioning using an accelerometer and experience sampling method on a smartphone. We analyzed the relation between daily physical activity level and a number of different properties of daily living (location, social component, activity type and the weekday). Five healthy older adults participated in the study during approximately one month. Our results show that location, social interactions, type of activities and day of the week influence significantly the daily activity level of the participants. Results from this study will be used in the further development of an unobtrusive monitoring and coaching system to encourage active behavior on a daily basis.

Keywords: monitoring · physical functioning · physical activity · daily living · older adults · experience sampling method

1 Introduction

The World Health Organization estimates that the percentage of world population aged above 60 will double between 2010 and 2050 from 11% to 22% [1]. The problem is particularly apparent in the Western world where it is expected that by 2060 approximately 30% of the population in the European Union will be aged above 65 years old [2]. Such demographic change brings socio-demographic

challenges, of which the increased burden on the healthcare system is one of the most relevant. It is expected that by 2060, 8.5% of the global GDP in EU-27 will be spent on healthcare and 3.4% on long-term care [3]. There is a growing trend towards developing technologies that aim to reduce the burden on health care systems by improving self-management skills and delaying institutionalization.

Frailty is an age-related condition with high prevalence worldwide. The exact estimates differ according to the definition of frailty adopted, with rates among community dwelling older adults varying between 7% [4] and 40-50% [5]. In this paper we use the following definition: “*frail elderly are] older adults who are at increased risk for future poor clinical outcomes, such as development of disability, dementia, falls, hospitalization, institutionalization or increased mortality*” [6]. Frailty can be associated with, but is distinct from, natural age-related impairments and it often predicts disabilities in activities of daily living [7]. Therefore, prevention of frailty relates to early detection of daily functioning decline. Daily functioning monitoring requires a multi-domain approach in which physical functioning is one of the domains addressed. Regular monitoring through conventional methods such as self-assessment questionnaires can be time consuming and troublesome. Technological developments provide reliable substitutes. From robotic companions to smart and caring homes, researchers are working on unobtrusive solutions to monitor the daily life of the elderly. Much of these solutions concern the home environment, while monitoring outdoors remains a challenge. Recent developments in ambulant sensing allow for easy monitoring physiological parameters such as physical activity or heart rate. Experience sampling (also known as ecological sampling) is also becoming a widely adapted method to study daily life.

The use of technology for health monitoring can be of value as a tool to create self-awareness as well as to improve the health care delivery through communication of the gathered information to health care professionals. Technology allows in-time alerts and interaction with the user, if necessary. Furthermore, the data acquired can serve as input to health behavior change recommendation systems, for example sending motivational messages that, based on the current status, encourage the user to adopt healthier lifestyles [8]. When designing technological interventions for the aging population one should take into account the multidimensionality in impairments of the target population and possible changes over time. As such, there is a need for personalized interventions that adapt to the health status of the user over time. Personalization is not a new term in healthcare. Concepts such as personalized medicine and personalized healthcare have been used in the literature when tailoring treatment to individual patients’ needs and characteristics [9]. Specifically in Telemedicine systems that aim to provide health services remotely, personalization can range from decision support systems to aid healthcare professional when selecting treatments [10, 11], to computer based health interventions to improve patient’s health conditions [12–14] and increase patients’ health literacy [15].

This paper presents the initial ideas for the development of an ambulant monitoring and coaching system that continuously monitors daily functioning of the older adults, physical functioning being one of the domains addressed. To do so, a pilot study was performed to investigate the relation between several determinants of physical functioning in a sample of robust elderly. The paper is outlined as follows. Section 2 refers to physical functioning monitoring on the daily life. A pilot study on ambulant monitoring of physical functioning is introduced in Section 3. Finally, a discussion of the results and insights for future work is given in Section 4 and conclusions of the work are stated in Section 5.

2 Physical Functioning Monitoring

Physical functioning is one of the domains contributing to daily functioning decline and also the focus of our study. As an initial step for our ambulant monitoring system, we analyze the relation between physical activity level and parameters of daily living as, for example, location and social interactions.

An active lifestyle is of great importance during the whole lifespan. Physical activity plays a crucial role in the prevention and management of chronic conditions [16] and the practice of physical activity only 1-2 times per week is associated with decreased mortality [17]. Physical activity has also shown benefits in improving mental health of older adults [18, 19]. Daily activities such as walking or cycling, household tasks, or playing games are seen as important contributors to the general level of physical activity. Physical activity can be monitored using self-administered questionnaires (e.g. PASE questionnaire [20]) or, unobtrusively, using wearable accelerometer-based sensors.

Besides the contribution of daily activities to the overall level of physical activity, changes in the daily living of the elderly can be a good indicator for daily functioning decline. Before disabilities in activities of daily living manifest (i.e. bathing, dressing, toileting, transferring, continence and feeding), older adults might, to some extent, change their extra activities — i.e. activities on top of what the elderly minimally need to do — as for example the leisure activities. Performance of leisure activities seems inversely related to frailty and positively related to delay of functional decline [21]. Daily living (or performance of daily tasks/activities) can be monitored through self-reported measurements as answering a validated questionnaire of (instrumental) activities of daily living (e.g. [22]). In this type of questionnaire, individuals are asked about their ability to independently perform activities such as shopping or laundry. This solution might be time consuming and cumbersome when applied for a long period of time. We support the idea of using a smartphone application to monitor daily living through Experience Sampling Method [23]. This method can be used to ask several questionnaires at random moments throughout the day regarding, e.g. current activities. With the experience sampling method it is possible to get an overview of the daily living of the participants as well as to obtain indices of behavior.

In the next section of this paper we describe a pilot study developed in the Netherlands which aimed at studying the relation between daily physical activity level of a sample of older adults and their daily living using a wearable sensor and a smartphone.

3 Pilot study

3.1 Methods

Five older adults aged 67.2 ± 2.3 years (3 female) participated in the study during 29 ± 3 days. Before the start of the experiment, the participants answered several questionnaires to assess the current health status. Among others, the level of frailty was assessed through two self-rated questionnaires — Groningen Frailty Indicator [24] and the INTERMED [25, 26], to guarantee that all participants were robust.

Daily Living – Three properties of daily living were assessed using the experience sampling method on a smartphone application (Figure 1): activity category (*what are you doing?*), location (*where are you?*) and social interaction (*with whom are you?*) (Figure 1). Questions were prompted approximately every hour from 08:00 till 20:00. A set of common activities (e.g. preparing food, eating, resting, and playing with children) was shown on the screen as well as the option to enter an additional activity. Common examples were also shown regarding location and social interaction.

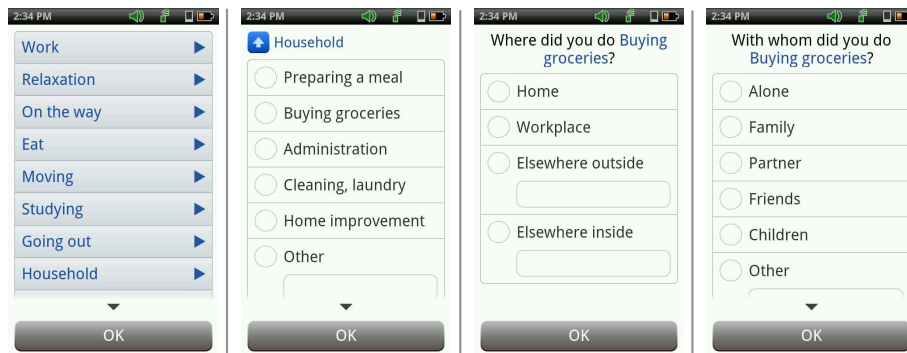


Fig. 1. Screenshots of the experience sampling application showing the hourly questionnaires.

Daily Physical Activity – Physical activity was assessed continuously over the measurement period with the Activity Coach, a system composed of a 3D accelerometer counting energy expenditure as the Integral Module of the Bodily

Acceleration (IMA) [27] averaged per 10 seconds intervals and a smartphone application [28]. Participants were told to wear the sensor from 08:00 to 20:00. No goal or feedback on the physical activity level was received during the experiment.

3.2 Data Analysis

The daily activity level day was defined based on the sum of IMA values for each day and it was represented by a nominal variable with three categories: ‘Inactive’, ‘Moderately Active’ and ‘Highly Active’. The K-means clustering algorithm was used to categorize the activity level of each day as it could adapt to each participant’s activity level in contrast to using pre-defined cutoff points for all participants.

Answers from participants were categorized as shown in Figure 2. Each set of questions answered was considered an **Event**. Each Event has four properties: **Location**, **Social Component**, **Activity Category** and **Time**, each having at least one possible value. After this categorization, the frequency of episodes with a certain value registered per day was calculated.

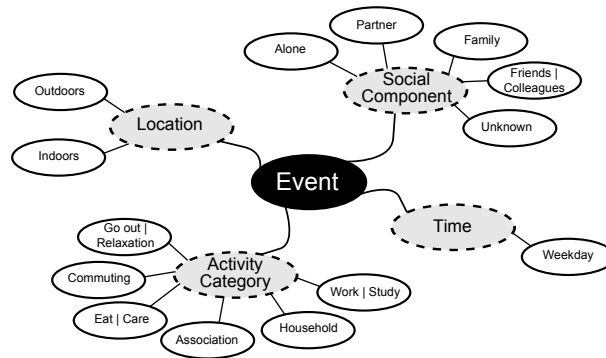


Fig. 2. Categorization of the answers provided on the smartphone. Each **Event** is a set of questions with four properties (*gray circles*) each. Every property has at least one possible value (*white circles*).

We investigated the relationship between physical activity level and daily living properties with Nominal Regression analysis. Variables associated at $p < .15$ were tested for their association with activity level with a Kruskal-Wallis test. Variables associated with the activity level were entered in the univariate Nominal Regression analysis. We did not perform multivariate analysis considering the clear dependency between the properties of the events (e.g. ‘commuting’ will always be performed ‘outdoors’). All statistical calculations were performed with SPSS statistical package.

3.3 Results

Participants have shown different levels of daily physical activity on the total of 146 days analyzed (Figure 3). Subject 3 was the least active amongst other participants while subject 1 and 5 were, on average, the most active. Moreover, the outliers in the boxplot suggest that there have been some days in which the participants had been highly physical active or have had a very sedentary behavior.

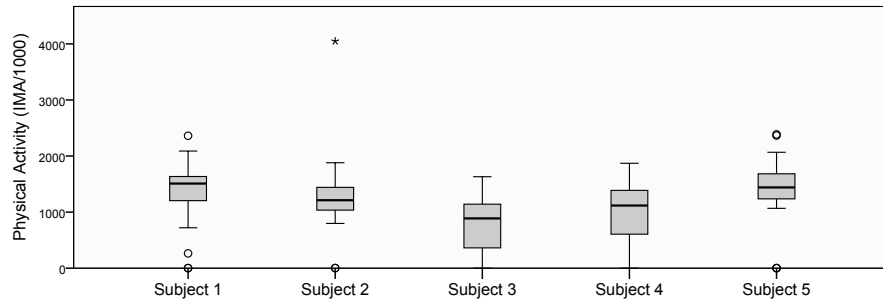


Fig. 3. Boxplots of daily physical activity in 5 subjects.

Each cluster centroid represents the average value of physical activity of a specific participant for a cluster and is tailored to the participant’s daily physical activity in the study period (Table 1). As an example, a daily physical activity value of 1000 can label the activity level of that day as ‘Moderately Active’ for subject 3, but will label the day as ‘Inactive’ for subject 2 due to his/her being generally more active. Table 1 also shows the frequency of days falling within each cluster.

Subject	Inactive		Moderately Active		Highly Active	
	Centroid	Frequency	Centroid	Frequency	Centroid	Frequency
1	935.9	30.3	1568.8	57.6	2085.6	12.1
2	1103.6	62.1	1602.6	31.0	3511.7	6.9
3	453.4	16.7	988.4	63.3	1535.4	20.0
4	436.3	23.3	1094.8	50.0	1609.9	26.7
5	1252.6	41.7	1564.1	41.7	2191.6	16.7
All	924.3	34.2	1560.6	49.3	2827.2	16.4

Table 1. Overview of results from K-means clustering showing the cluster centroids (in IMA/1000) and frequency (%) of days falling within the defined clusters. The last row shows the centroids and frequencies of each cluster when data from all subjects was considered.

A total of 1534 experience sampling (ES) points were collected. Participants reported most of their events at home (65.7%-82.6%). Regarding the social component, the majority of the events were reported as ‘alone’ (34.5%-52.8%), followed by ‘with partner’ (24.7%-56.6%), ‘family’ (5.0%-15.1%) and finally ‘friends or colleagues’ (6.8%-10.4%). The most frequent activity reported was ‘relaxation or going out’ (32.8%-40.5%), followed by ‘eat or care’ (20.7%-31.1%), ‘household’ (8.6%-23.3%), ‘commuting’ (7.7%-20.2%), and finally ‘work or study’ (0.7%-11.1%). Only two subjects reported ‘association’ activities (0.9%-1.3%) — i.e. participation in religious, political or sports associations. Figure 4 shows the relative frequency of the values registered for each one of the properties of daily living.

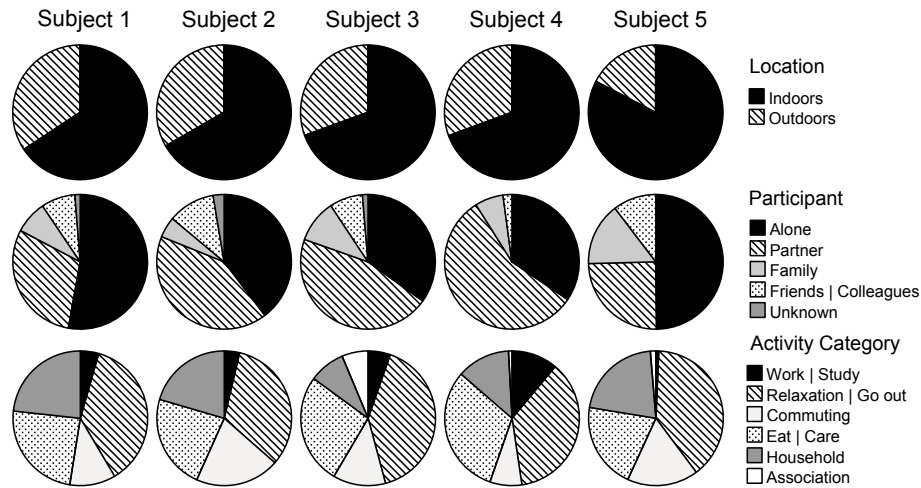


Fig. 4. Relative frequency (%) of values for each property and subject showing results of the reported categories from the experience sampling method.

Concerning the data from all subjects, ‘indoors’ (property *Location*), ‘friends or colleagues’ (property *Social Companion*), ‘work or study’, ‘relaxation or go out’, ‘commuting’, ‘eat or care’ and ‘association’ (property *Activity Category*), and ‘weekday’ (property *Time*) showed association with the physical activity levels ($p < .15$). Also, within each subject separately the association between the frequency of each value and physical activity level was tested, only minor changes were detected. The data of one of the subjects did not show any significant association between values of daily living and the physical activity level. Nominal Regression analysis was used to further analyze the relation between each one of the values aforementioned and the physical activity level. Considering that we are interested in predictors of physical activity in the daily living, “Inactivity” was set as reference in Table 2.

An increase in frequency events reported ‘indoors’ decreases the chance of having a highly physically active day compared to an inactive day. This means that days with higher frequency of events reported outside the home environment are more likely to be highly physically active days. An increase in the frequency of events with ‘friends or colleagues’ gave a 0.663 fold risk of ‘Moderately Active’ days compared to ‘Inactive days’. Concerning the Activity Category property, the frequency of events classified as ‘relaxation or go out’ had a 0.721- and 0.619-fold increased risk of ‘Moderately Active’ or ‘Highly Active’, respectively. The frequency of ‘Work’ events on a day had a 1.9 fold increased risk of ‘Highly Active’ versus ‘Inactive’. Finally concerning the property Activity Category, the frequency of ‘Eat and Care’ events on a day had a 1.475 fold increased risk of ‘Moderately Active’ versus ‘Inactive’ days. Regarding time, participants seem to be more likely to have ‘Moderately Active’ days at the end of the week. Within subject analysis resulted in similar results with a few notable cases. For one of the subjects, the frequency of events reported with ‘friends or colleagues’ gave a 3.836 fold increased risk of having a highly active day compared to an inactive day. For two subjects an increase in the frequency of being alone gives a higher chance of ‘Moderately’- and ‘Highly Active’ days compared to an ‘Inactive’ day.

Values	Moderately Active vs. Inactive			Highly Active vs. Inactive		
	OR	95%CI	<i>p</i>	OR	95% CI	<i>p</i>
Indoors	0.970	0.811-1.161	0.741	0.777	0.617-0.979	0.032
Friends Colleagues	0.663	0.480-0.915	0.012	0.896	0.628-1.279	0.547
Work Study	1.325	0.837-2.096	0.230	1.900	1.152-3.135	0.012
Relaxation Go-out	0.721	0.574-0.905	0.005	0.619	0.453-0.846	0.003
Commuting	1.023	0.764-1.370	0.877	1.393	0.975-1.991	0.069
Eat Care	1.475	1.031-2.111	0.034	1.276	0.801-2.032	0.304
Weekday	1.251	1.037-1.509	0.019	1.120	0.874-1.435	0.369

Table 2. Nominal regression analysis of the values from the experience sampling events vs. physical activity level.

4 Discussion

The aim of the pilot study was to investigate the relation between physical activity level (as either inactive, moderately active, or highly active) and daily living through a set of different properties of daily events reported on a smartphone. The first step of the data analysis consisted of clustering the physical activity data of each participant in three categories. Inactive days of subject 5 are almost three times more active than inactive days of subject 3 or 4. Similar

differences are seen in the other clusters. This justifies our choice in performing within-subject clustering analysis and emphasizes the need for developing personalized interventions to coach physical activity of the older population. Such applications should also adapt to the user following the behavior change over time.

The second step was the categorization of the events. Useful insights were gained into the daily life of the older adults during this phase. It is noteworthy that most of the events were reported in the home environment, suggesting that this might be a good place for interaction with the elderly users of a behavior change coaching system. Such a system can provide reminders or motivational messages at the right moment to increase adherence to the telemedicine platform and to facilitate behavior change in the older adults. In what concerns the social companion, looking at our results, most of the events were reported alone or with a partner. Other social interactions counted only for 8.9%-25.4% of the events. Socialization is mentioned as a motivator of physical activity by active and inactive groups in the study from [29]. This endorses the idea of recommending physical activity with peers as a way to encourage physical activity and stimulate social activities which are very important also in older age [30]. Regarding the type of activity, relaxation related activities count for a big part of the day. Only approximately half of the events reported related to eat, care, household or commuting. Knowing the time when these routine activities take place can also optimize the timing when a motivational message is sent and increase the compliance. Our results relate to a certain extent with the study performed by Chad et al. with 764 Canadian older adults, in which housekeeping activities had the greatest contribution to the PASE score [31]. The PASE questionnaire assesses physical activity level of the elderly by, among other factors, the time spent on occupational, household and caring activities [20].

Next steps in the development of the monitoring system include improvement of the sensing mechanism. During the time of the experiment the number of events reported per day varied but did not decrease over time. However, all the subjects were aware that the data would be used for research purposes and were motivated to finish the study. We believe that in normal daily life, without a research purpose, answering questions every-hour can be troublesome and lead to disuse of the technology after a certain period of time. Longer studies with monitoring of other parameters could be interesting to ascertain whether changes in daily living precede or succeed changes in health status. The results can be used to model participant's behavior and provide tailored recommendations on how to maintain a healthy lifestyle. Initial ideas for such a system are found in [32].

The present study has a number of limitations. The small sample size means that the participants might not be representative of the typical elderly population making our results inconsistent. However, the amount of data gathered per subject is large, enabling our detailed qualitative study. We have a total of 146

days of measured physical activity and a total of 1534 experience sampling events acquired. Therefore, we consider that our data is useful to receive insights in the daily living and physical activity of the older adults. Another limitation concerns the categorization of the events. Subjects were asked to report their daily events approximately every hour. In the first question they had to select the category of the activity. When analyzing our data we realized that the categorization is vulnerable to subjectivity, meaning that the same event can fall into a category for one subject and other category for other subject. For example, two subjects reported “taking care of the grandchildren” as “care” while others reported as “relaxation”. This means that the same activities fall into different categories according to the each subject. The fact that the data was acquired only between 08:00 and 20:00 can exclude relevant data. In any case, we consider that our study is relevant for getting insights on diurnal behavioral of older adults.

5 Conclusion

In this work we studied physical activity and daily living in a sample of robust older adults. We underline the importance of learning physical activity levels from personal data instead of using general cut-off points when studying the older population. Our results show that location, social interactions, type of activity and day of the week significantly influence the daily physical activity of the participants. Instead of motivating people to get physically active, a coaching strategy could thus be to motivate people to engage in outdoor- or social activities, increasing physical activity indirectly. This *motivation by proxy* could add to the diversity of coaching of such systems and potentially increase adherence and pleasure in using the system.

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