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Behavioral anomaly detection system for the wellbeing assessment and lifestyle support of older people at home

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Abstract

The wellbeing assessment of older people is becoming crucial in today's era of aging and home care in order to provide the best possible care. New technologies are being used to assist older people at home, which generates an extensive amount of health and wellbeing information. The application of artificial intelligence algorithms to this healthcare and wellbeing data can enhance patient care and provide support to professionals by reducing their cognitive load. These algorithms can detect anomalous physiological, physical, and cognitive conditions in older individuals, which can help to identify emergency situations, or the early detection of an emerging health condition. However, while there has been relevant research in the field of anomaly detection for various engineering applications, there is little knowledge about healthcare and wellbeing-related anomaly detection. To this end, in this article, we propose an innovative system for detecting behavioral anomalies for older people that are being monitored at home with the aim of improving their lifestyle and wellbeing as well as the early detection of any physical or cognitive condition.

Keywords: Anomaly Detection; Artificial Intelligence; Active Aging; Home Care; Healthcare and Wellbeing; Older Adults' Monitoring

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1. Introduction

The aging population coupled with the increased demand for home care services in recent years has placed greater importance on being able to easily and effectively assess older adults' wellbeing in order to provide them with the highest quality support [1]. Currently this assessment is being carried out using new technologies, such as portable physiological signal-monitoring equipment, wearable health parameters monitoring devices, or patient-centered mobile/web applications as part of information and communications technology (ICT)-based systems [2]. As a result of using these technologies, a great amount of health and lifestyle information is being generated and obtained from the monitored individuals. This data can be very useful to better understand the evolution of patients' health and thus assist caregivers in the decision-making processes for their patients' wellbeing and lifestyle [3]. This can be achieved by the application of artificial intelligence (AI) techniques to the data in order to analyze and obtain conclusions. In addition, it would be possible to develop models to make predictions or detect anomalies in patient's state of health and wellbeing. While predictive models are being used more frequently in healthcare systems, to our knowledge, extensive information about the use of anomaly detection systems (ADSs) in this field is not available yet. Even so, using AI algorithms to detect anomalous conditions of patients can assist in identifying emergency situations or the early detection of health problems, which can help caregivers to better assess their patients' wellbeing. In addition, data gathered in these scenarios is usually unstructured and changes from day to day, which makes the use of AI techniques beneficial for the analysis of this kind of data.

The detection of anomalies, also known as outliers, can be practiced in a variety of healthcare fields, which can cause the word anomaly to take on different meanings. For example, an anomaly can indicate a decompensation or functional deterioration of an organ, such as the heart. However, for the purpose of this paper, we consider that anomalies are referring to alterations in the behavior or physiological parameters of an individual, such as a considerable decrease in the number of steps walked per day.

Therefore, our paper proposes a system for detecting anomalies in the behavior of older adults while they are monitored unobtrusively at home to assess their wellbeing and provide them with support for lifestyle improvement. Quality of life for older individuals heavily depends on several factors such as nutrition, physical health, the ability to perform activities of daily living, lifestyle, and psychological health [4]. Moreover, as these factors are associated with health determinants such as frailty (an important aging-related syndrome of physiological decline, characterized by marked vulnerability to adverse health outcomes), it is important to investigate the influence of these factors in relation to psychological and health status. This is in fact the main novelty addressed in our work, the detection of anomalies using AI methods in this type of health-related data or parameters.

This paper describes the design, the initial methods, and the results of the proposed system in the context of the development of an intelligent platform for supporting older adults and their caregivers in the management of their wellbeing. For that, the paper is structured as follows: first, the state of the art in the research field is analyzed; then, the materials and methods proposed for the development of the solution are described; and finally, the results and conclusions of the development, and future research lines are explained.

2. Related Work

The use of technology by and for older adults has started to become a prevalent topic in the last decade [5, 6]. As the older population grows, the research surrounding technology usage by and for older adults is also expanding, intending to promote their wellbeing and lifestyle support [7]. In this context, different studies have explored the relationships that older adults have with everyday digital technologies, showing that they can have an impact on older adults' feelings of loneliness and wellbeing [8].

A modern and clear example of ICT for the promotion of wellbeing is using smart digital solutions (i.e., smartwatches or smartphones) [9]. With these technologies, patients can be monitored continuously, and thus a large variety of parameters can easily be measured. In view of this, different approaches have used this type of data to analyze and obtain information or design models to predict and prevent patient health-related problems. For instance, a recent study [10] investigated the correlations of subjective and social wellbeing with sedentary behavior and physical activity (PA) in older adults, and they suggested that older adults with higher levels of subjective and social wellbeing spend less time sitting and engage more in PA. A similar approach [4] investigated the associations between psychological distress and diet patterns when adjusting for different lifestyle behaviors, wellbeing, health status, physical functioning, and social support in older people. They concluded that understanding the influence of diet patterns in relation to psychological distress provides valuable insights into how society can promote healthy lifestyles for an aging population, e.g., by increasing older people's food and nutrition knowledge.

Although many approaches have obtained conclusions and usable information from this data [11, 12], fewer studies exist regarding the use of this information for developing models to detect, predict, or prevent patient health-related problems or about integrating said models into patient healthcare systems. In fact, in a previous study presented by our research department [13], a system capable of predicting heart failure patients' decompensation in real time was developed to prevent future admissions/readmissions using AI techniques. Further in relation to the present work, a recent study focused on the COVID-19 pandemic [9] demonstrated that providing an affordable user-friendly ICT-based companion for older adults at home could identify the psychosocial and behavioral disorders as well as risk factors in the target population. In addition, these tech companions could deliver personalized recommendations, and mitigate psychosocial strain in older adults. Hence, given the need for urgent implementation of technology-based systems for the wellbeing assessment and lifestyle support of the older population, our paper proposes an AI-based digital solution for detecting behavioral anomalies and predicting possible health complications in older adults.

Anomaly detection is used in a variety of engineering sectors such as civil infrastructures' structural health monitoring [14], or even healthcare applications' functionality [15], but little is known about its potential use in patient data analysis. In the last few years, studies about anomaly detection in patient cardiac activity have been carried out by analyzing electrocardiogram (ECG) signal data [16, 17]. Results demonstrate the ability of these approaches to detect anomalies in heart rate data and they support that the use of AI techniques can help health practitioners to detect anomalies earlier and more accurately. Nevertheless, this type of patient data (physiological signals) is different from the data that is captured in our work (wellbeing and lifestyle parameters), and therefore, ADSs used in the mentioned studies are not suitable for this data. In fact, other studies have demonstrated the effectiveness of different algorithms in detecting anomalies in data collected from wearable medical sensors [18, 19]. Although there have been researchers that have addressed this particular issue in their recent study by presenting an approach for recognizing anomalies in the activity of daily living of an older adult living alone [20], they only measure the inactivity and activity periods of the different activities (sleeping, eating, watching TV), without considering any wellbeing or lifestyle parameter, such as daily steps, heart rate values, weight, etc.

In this sense, we take into account the aforementioned studies for the development of our work, a novel behavioral ADS for the wellbeing assessment and lifestyle support of older people at home, in the context of two projects. On the one hand, SERWES is a local project funded by the Basque Government which aims to develop new services to improve the sustainability and the quality of care for older people living in nursing homes. In this sense, this project is focused on using wearables and IoT sensors for the early detection of diseases or behavioral disturbances. On the other hand, the European SHAPES project [21] aims to support and extend healthy and independent living for older adults who are facing permanently or temporarily reduced functionality and capabilities. More specifically, it integrates a cluster of digital solutions, including assistive robots, eHealth sensors, and wearables, Internet of Things (IoT)-enabled devices, and mobile applications that will be deployed in a Pan-European Large-scale Pilot Campaign, involving 2,000 older adults, caregivers, and healthcare service providers.

3. Materials and Methods

To reach our objective of providing caregivers and healthcare professionals with a tool capable of detecting anomalies in the behavior of older adults, two development phases are defined: i) an initial phase for the design of the system and the implementation and testing of a prototype (described in this paper), and ii) a final phase for the development of the final system and its validation with end users. In the initial phase of the development of our work, the general design of the system, the prototype design and implementation, the data model, the visual analytics proposal, and the validation plan were carried out.

3.1. System design

As presented in Fig. 1, the general design of our proposal for the older individuals' follow-up consists of an ADS integrated into a patient-centered platform. This system receives a variety of older adults' information as input for its analysis and processing, and supplies providers (i.e., end-users) with different tools for the decision-making process in the management of their patients' healthcare and wellbeing as output.

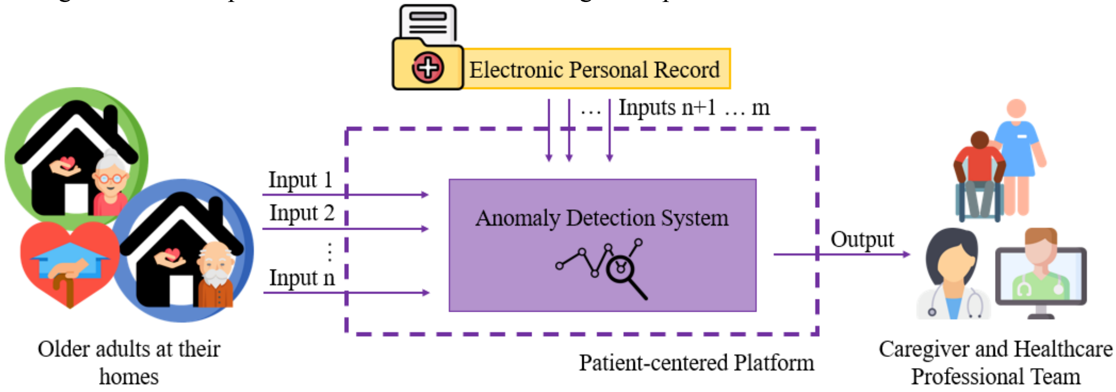


Fig. 1. Diagram of the general design of the system.

The inputs received to the ADS have different origins. On the one hand, data about the activities of daily living (ADL) of the older adults monitored at their homes are collected using a variety of devices and sensors described in Fig. 2. On the other hand, where possible, the information obtained from the users' Electronic Personal Records (EPRs) including both healthcare and wellbeing information is used as well.

All data is then analyzed and processed by the ADS. The technology the ADS employs is based on AI methods that will learn patterns from unlabeled data or find some structure in it, being the logic that our type of data (unstructured data) needs for detecting irregularities in it. Given that there are various types of algorithms in ADSs, (rule based, classification based, clustering based, nearest neighbour based, statistical, etc.), we will apply the optimal algorithms which generate the best results for each of our projects (SERWES and SHAPES).

As outputs, apart from the alerts of the detected anomalies and the corresponding visual analytics tools described in section 3.5, the system classifies the state or behavior of each individual using the three traffic light colors as follows:

- Green – Everything is ok, usual condition/behavior.
- Yellow – Suspected anomaly in health/wellbeing status, the follow-up team proceeds to study the case and assesses possible measures to be taken (observation, urine dipstick, medication adjustments, etc.)
- Red – Alert, clear behavioral deviation, the follow-up team addresses the case urgently.

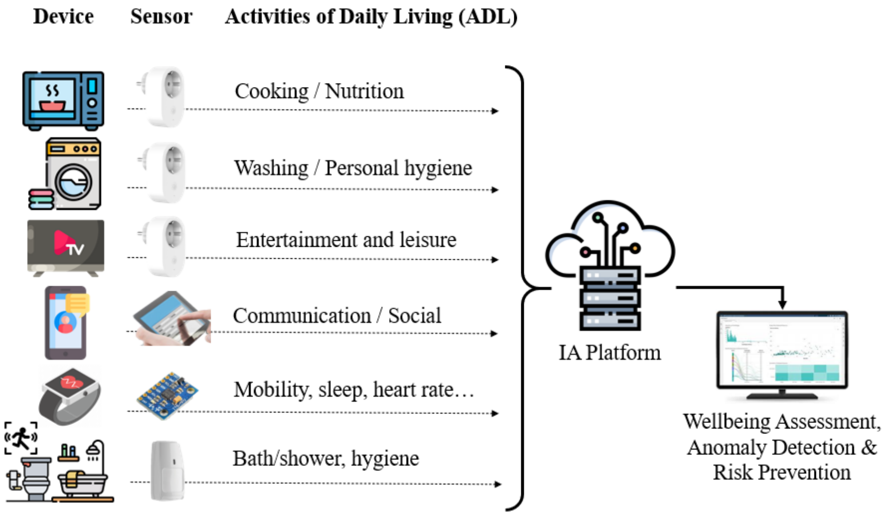


Fig. 2. Scheme of the system components.

The methodology proposed for the development of the general system follows four main steps. First, an initial prototype is designed and developed, which is described in sections 3.2 and 3.3. Second, an initial dataset is created containing the information obtained from the wearables, which were used by our development team members in their daily activities. Once the initial dataset is prepared, the performance of the prototype is tested, evaluated, and improved iteratively. In addition, the possibility of using other AI techniques for the model is addressed as well. Lastly, the final prototype is integrated into the project platform and validated with the end users.

3.2. Prototype design

The initial prototype of the ADS (see diagram in Fig. 3) is based on the detection of irregularities in the normal patterns of physical activity-related data of the users. For that, the users are supplied with wearable devices (i.e., wrist bands) for their activity tracking. Each wearable is connected to a gateway installed in the respective homes of the users for the data transferring process. At the same time, these gateways send the information to the database in the server, from which the AI model gets the necessary data for its processing and the detection of anomalies. Finally, the obtained results are provided to the caregiver and health professional team through a dashboard for their visualization and management.

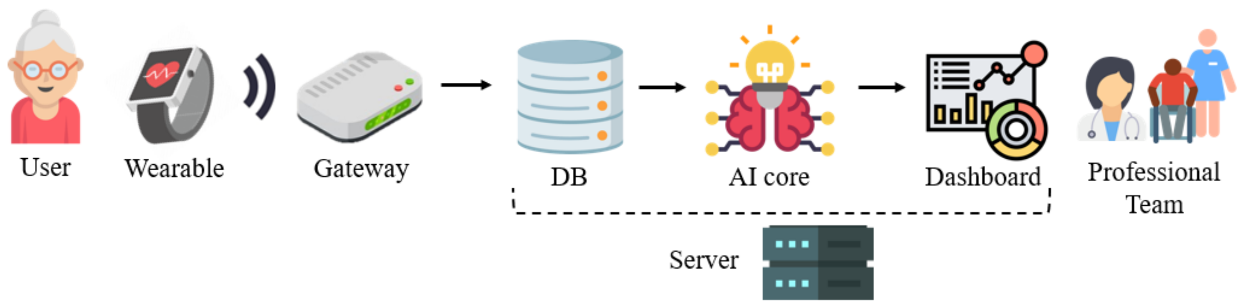


Fig. 3. Diagram of the prototype design.

The next table (Table 1) describes the requirements of each of the components that compose the prototype at the design level.

Table 1. Requirements of the prototype components.

Component	Requirements
Wearable	It needs to collect a variety of physical activity data from the user, such as daily steps, heart rate values, daily calories, or sleep data. Besides, its software must allow access to its data via an open API for the management of the information by our system. The design, style, waterproof capability, autonomy and recharge frequency of the batteries and the comfort of the device are also considered.
Gateway	This equipment needs to connect to the wearable via Bluetooth and collect its information by configuring the necessary libraries and applications in the gateway system for the preprocessing of the gathered data. Also, it must be suitable for installation in the users' homes or nursing homes.
DB	The database needs to be able to be configured to correctly receive the information from the gateway and send the requested data to the AI-based API.
AI core	The AI-based model needs to detect anomalies in the type of data collected by the system, i.e., in physical activity data.
Dashboard	Apart from being able to visualize all the analytics of the users' data, it must offer tools to the health professional team for the management of their patients' health and wellbeing state.

3.3. Prototype implementation

To obtain the initial dataset and make the testing of the initial model, it is necessary to implement a prototype. For this process, the technologies used for each of the components which comprise the prototype are selected considering the requirements described above (see Table 2).

Table 2. Technologies of the prototype components.

Component	Technology
Wearable	The selected device is a wrist band called Xiaomi Mi Band 4[1]. Huami is the exclusive provider of wearable technology for Xiaomi and maker of the Mi Band, and it provides an API for accessing user activity data tracked with Huami wearable devices. The band has also been chosen for its characteristics: o Fancy design, robust, comfortable, and water-resistant. o Pedometer integrated for measurement of number of steps, distance, and calories burned. o Indoor and outdoor activity tracker. o Heart rate monitoring: automatic detection method, frequency values to select of 1, 5, 10, or 30 minutes. o Sleep tracker based on the movement variables from falling asleep to sleeping to waking up (light and deep sleep tracking, measurement of total sleep hours). o Long battery life (up to 20 days on a single charge). o Cost-efficient (official price of 34,99€).
Gateway	For this function, a Raspberry Pi (the RPi 3 Model B+[2] in particular), a small single-board computer, has been selected. This device permits the connection with the Mi Band via Bluetooth (Bluetooth 4.2, BLE) and the necessary libraries and applications following the methodology[3] provided by the University of Castilla–La Mancha (UCLM) can be configured to receive the information from the wearable. In addition, this data can be stored in the database using internet connection, which can be configured via Ethernet or Wi-Fi connection.
DB	The system chosen for the management and configuration of the database is PostgreSQL or Postgres. It is a free, open-source, object-relational system with very good, demonstrated results in terms of reliability, feature robustness, and performance.
AI core	The AI technology of the system is based on a selection of different time-series anomaly detector models, implemented in open-source libraries written primarily in Python language. The model implementation consists of a strategy of time-series prediction and anomaly score calculation.
Dashboard	The web/mobile application for the caregiver and health professional team is developed in Angular. This framework is also open-source and is based on TypeScript, a language that allows the user to design elaborate applications easily and efficiently.

[1] https://www.mi.com/global/mi-smart-band-4/
[2] https://www.raspberrypi.org/products/raspberry-pi-3-model-b-plus/
[3] https://arcogroup.bitbucket.io/shapes/integrating_miband_with_smart_mirror/

The prototype has been implemented and a picture of it is shown next (Fig. 4).

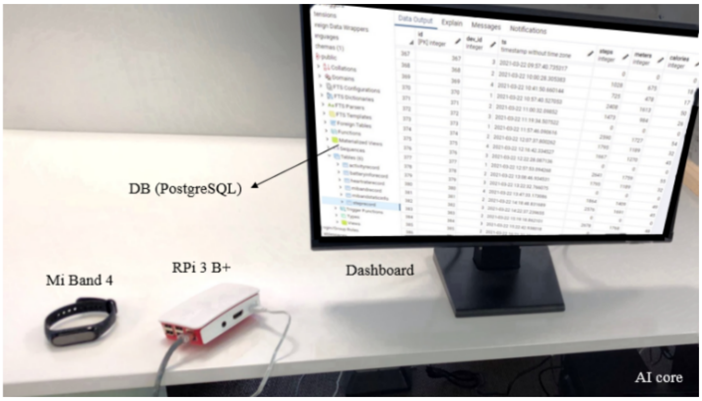


Fig. 4. Implemented prototype.

3.4. Data model

The parameters collected by the wearable device define the initial data model. In the next table (Table 3) the variables of the initial data model are described. Each variable generates values according to the sampling time (e.g., 1 minute, 10 minutes, etc.), and producing a time series of data per day.

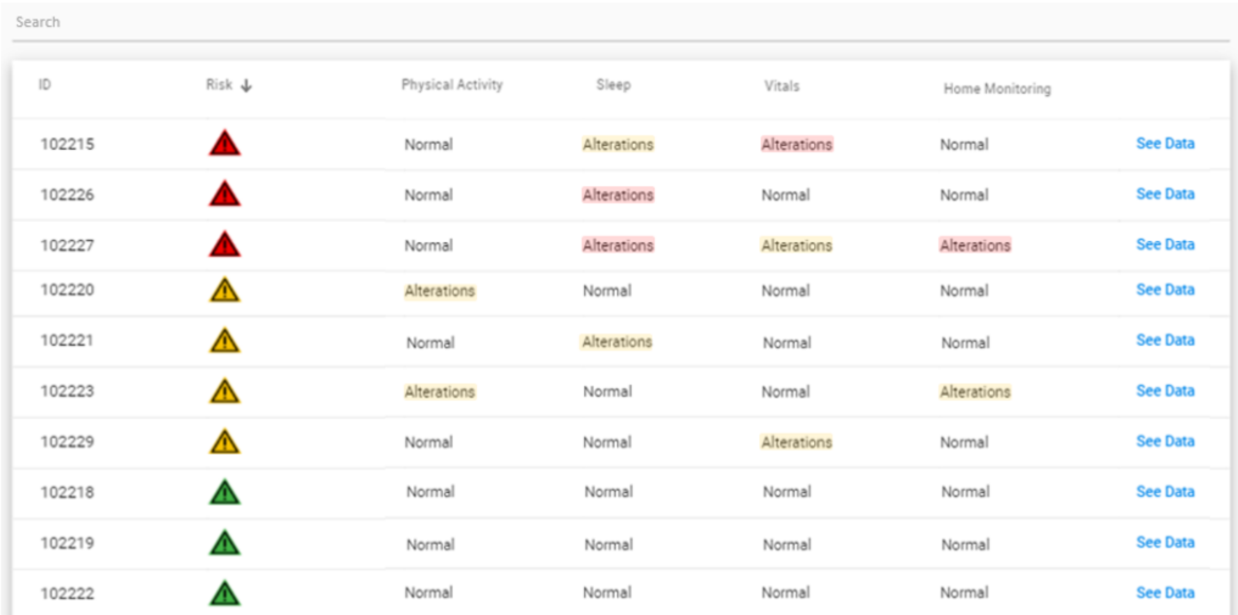
Table 3. Description of the variables in the data model. (*) Anthropometric information must be provided in the Xiaomi App (Mi App) to obtain these values.

Field	Variable	Description	Unit/Scale
Daily Step-related Information	Steps	Total daily steps until that moment	Integer
	Meters (*)	Total daily meters until that moment	Integer
	Calories (*)	Total daily burned calories until that moment	Integer
Heart Rate Information	Bpm	Value of the measured heart rate at that instant	Integer (bpm)

This data model will be expanded in future versions of the system using i) data obtained from the EPRs of the older adults participating in the study, ii) information about the use of domestic appliances, and iii) information obtained from personalized questionnaires and chatbots.

3.5. Visual analytics

For the visual analysis of the collected users' data, the healthcare professional team relies on a web dashboard where two different user interfaces can be distinguished. On the one hand, in the first user interface the list of all monitored users sorted by their risk type is visualized (see Fig. 5). The individuals with higher associated risks are displayed first. For that, colored signals representing the risk level of each individual are shown in a column, as well as the assessment domains (tracking fields) in the other columns showing if they are altered or not. Clicking the button at the end of each row, the professional can see more details about the health state of the patient by interacting with the second user interface of the platform.



Search

ID	Risk ↓	Physical Activity	Sleep	Vitals	Home Monitoring	
102215		Normal	Alterations	Alterations	Normal	See Data
102226		Normal	Alterations	Normal	Normal	See Data
102227		Normal	Alterations	Alterations	Alterations	See Data
102220		Alterations	Normal	Normal	Normal	See Data
102221		Normal	Alterations	Normal	Normal	See Data
102223		Alterations	Normal	Normal	Alterations	See Data
102229		Normal	Normal	Alterations	Normal	See Data
102218		Normal	Normal	Normal	Normal	See Data
102219		Normal	Normal	Normal	Normal	See Data
102222		Normal	Normal	Normal	Normal	See Data

Fig. 5. Example of the ADS user interface displaying the list of older adults sorted according to risk type.

The second user interface provides the caregivers with a visual analytics tool to see in greater detail the reasons for the alterations in the health or behavioral parameters of the individuals through the representation of each parameter's values in time. Fig. 6 presents an example of the graphs and visualizations that the caregivers could see. This tool obtains the necessary data from the DB employing different HTTP requests. As can be seen, the possibility to compare parameters or variables with each other is provided by visualizing more than one parameter in the same graph. In addition, alerts of detected anomalies or irregularities are indicated in a visual way classifying them as high (red) or low (yellow) risk anomalies. This classification is made by the AI model in the anomaly score calculation by configuring the thresholds of the two risk levels.

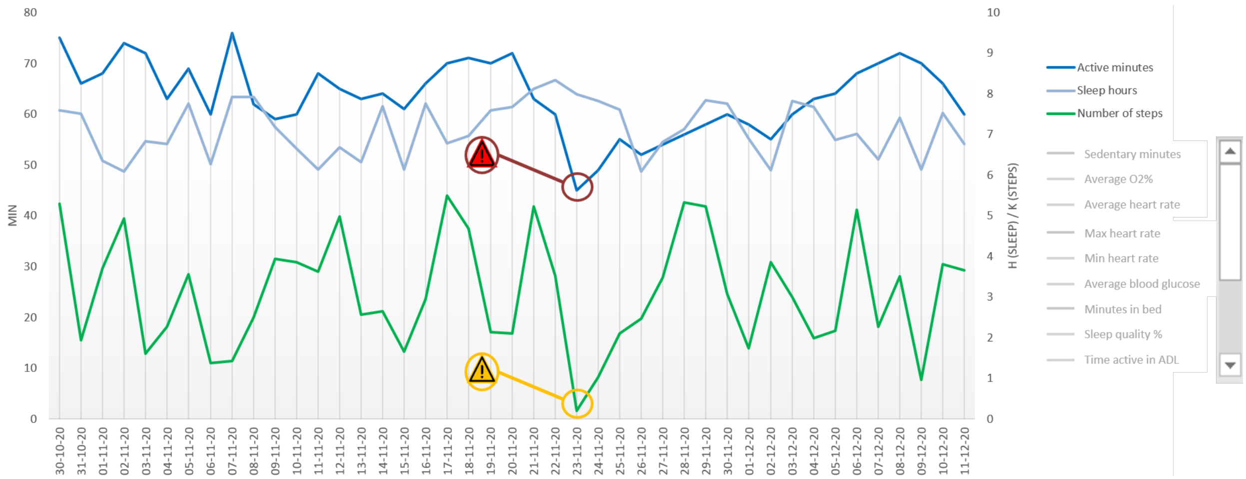


Fig. 6. Example of the visualization of two detected anomalies in the ADS user interface.

3.6. Validation plan

The proposed ADS will be validated in the following two relevant environments:

a) Nursing home.
Our system will be installed and validated in a real nursing home called Berra Nursing Home, owned by DomusVi, in Donostia-San Sebastián, Spain[4]. The validation is divided into three stages. First, four residents will wear the activity trackers for six months. The gateway will be installed in a common living room and the main goal of this first stage consists of real data gathering. Second, the collected data will be analyzed, processed, and different AI methods will be trained, compared and the best one will be selected. In the third stage, the final system will be piloted at Berra for an additional six months. In this final stage, healthcare professionals at the nursing home will use the system and the real anomaly detection capabilities will be assessed. This validation will be carried out in the scope of the SERWES project.

b) Smart Living Environment for Healthy Ageing at Home.
In this pilot theme, the consortium will create a platform for older adults living with permanent or temporarily reduced functions or capabilities which will enable a healthier, more independent, and more active living at home. Providing this platform will also ensure that the older adults remain integrated and continue to be active participating members in their community and social circles. In particular, the ADS will be tested to allow supporting and extending active and healthy aging and independent living, for the early provision of healthcare and wellbeing interventions and for delaying the need for institutionalization. This validation will be carried out in the scope of the SHAPES project.

4. Discussion

The aim of our study is to develop an innovative and promising system to detect behavioral anomalies for older adults that are living in their homes or in nursing homes. The system seeks the early detection of risky situations that may lead to healthcare conditions, or relevant wellbeing or behavioral disturbances.

In recent studies regarding anomaly detection in data collected from wearable medical sensors [19] or in the daily living activities of older people living independently [20], researchers do not use AI techniques for anomaly detection (although they do make use of different problem-solving algorithms), nor do they consider monitoring the wellbeing of their users. In our study, different AI methods will be implemented to detect behavioral- and health-related anomalies, basing our investigation on the results of recent approaches to detect anomalies in heart rate data [16, 17], which support that the use of AI techniques can help healthcare practitioners to detect anomalies earlier and more accurately.

Furthermore, although there is extensive research that aims to improve the lifestyle and wellbeing of older adults, our proposal provides an innovative approach in this particular area, offering a comprehensive and intelligent system capable of detecting anomalies in parameters related to both the physical and psychological behavior or state of users.

5. Conclusion

In this paper, the selection of the main technologies for the development of a behavioral anomaly detection system for older adults and a first implementation of the prototype are described. The proposed model uses artificial intelligence methods to automatically identify situations that are outside of the normal activity patterns of the monitored patient. Different anomaly detector models will be tested, and the ones giving the best results for each project will be implemented.

The results of these models are provided to the caregiver and healthcare professional team through a dashboard with visual analytics tools. This platform uses graphs for the representation of older adults' monitored information and the detected anomalies are notified as low or high-risk alerts in them. In addition, adding more than one variable to the same graph allows for the comparison of multiple variables, detecting the consequences of the anomalies, and helps health providers to identify the real problem.

[4] https://www.domusvi.es/residencia-mayores-guipuzcoa-san-sebastian-berra/

Additionally, an ambitious validation plan is currently ongoing in a real nursing home. Four residents in Berra Nursing Home, DomusVi, in San Sebastián, Spain, are using the system to gather initial data and to optimize the AI-based algorithms to use. The number of residents will be increased up to 20 residents in the following months. In parallel, a second additional validation is planned with a set of older adults living independently at their homes with permanent or temporarily reduced functions or capabilities.

6. Future Work

The next steps in the development of the study will be the key for the final validation of the prototype and thus, obtaining an anomaly detection system able to assess and support the wellbeing and lifestyle of older adults at home effectively and reliably. In this regard, first, a validation of the proposed system with real users and healthcare providers will be carried out. Next, the data gathering protocol will be extended by including more variables to be monitored, such as data related to the use of household appliances or information from questionnaires. Also, more pilots of longer duration in about fifteen to twenty homes in the scenarios of our two projects will be performed. Finally, the results obtained from these pilots will be published in future dissemination activities.

Acknowledgements

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