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► **To cite this version:**

Laura Maligne, Eric Campo, Adrien van den Bossche, Nadine Vigouroux, Frédéric Vella, et al.. Monitoring and Sensing System for People’s Behavior During Fall Events Based on Mobility Analysis. Innovation and Research in BioMedical engineering, 2025, 46 (4), pp.100895. <10.1016/j.irbm.2025.100895>. <hal-05220716>

HAL Id: hal-05220716

<https://hal.science/hal-05220716v1>

Submitted on 23 Apr 2026

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Original Article

Monitoring and Sensing System for People's Behavior During Fall Events Based on Mobility Analysis

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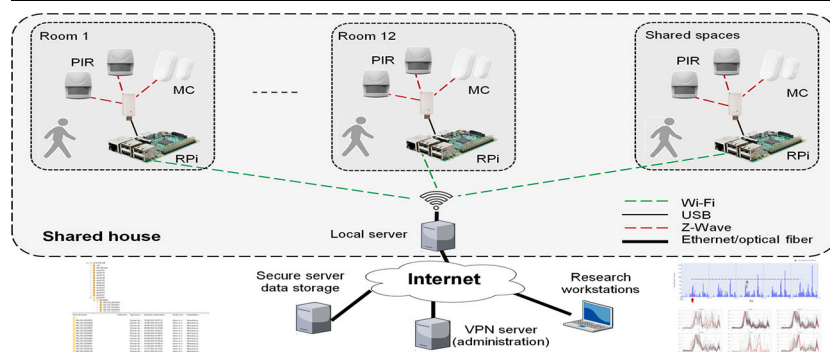
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HIGHLIGHTS

- Continuous monitoring of behaviors in an elderly shared home.
- Observation and analysis of behavior before and after a fall and return home.
- Less intrusive sensors network to collect real data of mobility.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:

Received 2 October 2023

Received in revised form 23 March 2025

Accepted 23 May 2025

Available online 30 May 2025

Keywords:

Motion sensors
Behavior model
Fall
Elderly people
Shared home

ABSTRACT

Objectives: Observing the activities of the elderly in natural life is a crucial issue nowadays to better understand their potential behavioral changes and predict risks. To this end, a comprehensive hardware and software infrastructure has been designed by a multidisciplinary team of researchers and pre-tested in a smart flat lab. It enables to collect relevant data and develop algorithms to analyze activities and detect changes such as falls, wandering or other risky situations. This study was carried out in a shared house by 12 independent elderly people. The study focuses on episodes of falls in the house, and analyzes mobility behavior before and after falls to observe the person's rehabilitation in the home.

Materials and Methods: Each resident's room and the two shared spaces were equipped with motion and magnetic contact sensors to record movements and entry/exit activities. 9 months of data were collected and analyzed, highlighting patterns of activity and changes in these behaviors, particularly when a fall occurred and then when the usual behavior returned, if at all. Two levels of analysis were implemented: the detection of deviation in activity indicators for each individual, and the detection of drift in the established behavior pattern over time. The classification technique used to extract the patterns is the K-means partitioning algorithm. We also used the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method to validate the performance of the K-means method.

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Results: Data analysis was carried out on the 4 falls recorded during the observation period, involving 4 of the house's occupants. The results highlight the relationship between model conduct and events related to falls and returns from hospitalization. Detection was validated by share house carers' annotations, acting as a ground truth, on the days when falls occurred. The first results of pattern recognition with clustering methods show that the K-means method provides more convincing results than the DBSCAN method. In this study, by observing the movement signals of residents who fell during the course of the study, we were able to identify characteristic post-fall behaviors.

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1. Introduction

1.1. Technological context

The living arrangements of elderly people living alone are among the major current concerns in the field of independent living. Many works have been realized for many years on the monitoring of the behavioral activity pattern of elderly living alone at home or in institutions using both wearable and embedded sensors. The use of sensor technology in elderly care has shown positive effects in various aspects of well-being, for example, identifying falls [1] and recognizing an elevated risk of falls [2] and noticing deterioration in general health through the monitoring of daily activities [3]. Currently, many different types of activity-tracking sensors exist on the market [4], e.g., wearable sensors like smart watches and wristbands and necklaces, pedometers [5], along with ubiquitous technology (ambient sensors) like motion and depth sensors, activity sensors, video cameras, temperature and humidity sensors as well as sound sensors [6]. Technologies have been seamlessly integrated into different aspects of people's life and reshaped people's health-seeking activities. They can collect continuous biological, behavioral, and environmental data; deliver health interventions; and measure users' health outcomes [7].

The range of methods and algorithms applied to detect human context and behavior is extensive and varies regarding several concepts. The adoption of these processing methods has a decisive impact on the accuracy of the final results. We can classify techniques into three categories: probabilistic and statistical techniques, computational intelligence techniques, and knowledge-driven techniques. Statistical techniques are the most commonly used techniques for modeling human behavior in the field of healthcare. They were used to find dependence and correlations between temporal information captured by sensors and the subject's estimated behavior. Methods like hidden Markovian models (HMM), Conditional random fields (CRF) and Bayesian networks are probabilistic reasoning concepts derived from statistical inference processes [8]. Probabilistic methods were commonly used for modeling behavior, due to their ability to present random variables, dependence and temporal variation between collected data [8]. Computational intelligence techniques are widely used in the literature as an alternative to statistical methods. These techniques, such as neural networks, support vector machines (SVM), data mining, decision tree and fuzzy system, were used to recognize activities, distinguish between normal and abnormal behavior patterns, and predict human behavior and health conditions [9,10]. Artificial Neural Networks (ANNs) have been widely used in the field of intelligent computing. They represent a mathematical tool in the artificial intelligence field that provides robust self-learning ability for data classifications [11]. Moreover, the authors explained that ANN, K-Nearest Neighbor (KNN), and SVM classifiers were computationally expensive although they provided good performance. Clustering methods such as K-means clustering, Fuzzy C-means (FCM), Self-Organizing Maps and K-Nearest Neighbor (KNN) are unsupervised techniques that can be used for modeling human behavior, the recognition and detection of abnormality. K-means is

a widely known and used clustering technique that delivers training results quickly [12]. Knowledge-driven techniques are another approach used for modeling human behavior. The approach makes observations about the real world, where most human activity is routine and the sequence of actions are similar to each other. The most popular techniques used for this approach are Rule-Based, Case-Based, Fuzzy logic, and Ontology-Based Reasoning [13,14].

The choice of techniques used is justified in section 3.3.

1.2. Aim of the study

Today, alternative housing to retirement homes exists and is developing in both rural and urban areas, but no study has examined the contribution of technology to these types of housing. The architecture of the premises, the geographical location, the profile of the residents and the legal structure differ from one type to another. Intergenerational residences, shared habitats, grouped habitats, community homes and collective flats are just some of the names given to this new residential offering, which is mainly for the people over 60 [15]. Shared Home (SH) is a new type of home for vulnerable independent elderly people, conceived by professionals after extensive experience in the field. Since 2009, this alternative facility has been designed to meet the needs of frail people who want to live at home for as long as possible without being alone and isolated. They live together in a small group of people and receive daily support from a professional. SHs exist in several forms in Europe [16]. People can participate in community life and express their social skills. However, even if residents are assisted and supported 7 days a week from 9 a.m. to 5 p.m., risks remain. In the evenings and at night, people are not helped if they have a problem. Each resident has to rely on himself or herself, or on other residents if necessary. Yet current technologies, already tried and tested in other environments, could provide an effective solution for modeling and understanding their lifestyle [17]. It could help prevent certain risks while respecting local lifestyle choices. The usual method used to monitor the activity rhythms of the elderly is to observe habitual behavior patterns and detect deviations from these patterns. Indeed, the behavioral activity pattern is a behavioral and biological 24-hour rhythm. Ageing, diseases, accidents and memory disorders can change this pattern.

The purpose of the study described is to present the technical system deployed in a shared house managed by ASF [18], a French organization based in the department of Tarn (81), and to analyze data collected. Over a one-year study period, project involves the objective measurement of behaviors through the study of mobility [19], sound environment analysis [20], and the use of voice and touch control [21]. One of the key issues is how to combine these various and unsynchronized measurements to identify habits, unusual signs and indicators of change in behavior. In this article, we focus on the first results on the modeling of mobility habits based on movement and entry/exit sensors that we have linked to the comments of carers.

We choose to focus on falls that occurred during the observation period. The consequences of a fall, besides physical fragility (fracture, discomfort), are the risk of unwanted isolation due to

limited mobility [22]. Before and after a risk event, the aim is to detect changes by observing mobility in rooms associated with an SH resident.

Continuous monitoring of the activity of more fragile populations using machine learning is raising increasing interest, and has the advantage of being adaptable, efficient in processing a wide range of information and parameters, and can be automated if proven to be robust. Several longitudinal monitoring studies using AI tools have been carried out with other parameters, such as images from thermal and depth cameras [23], or with the development of an alert system for an elderly population living alone and not requiring outside assistance [24].

Based on the modeling of habits using AI-based learning techniques, we can monitor changes in residents' behavior (in this study, we are particularly interested in bedroom activity) and analyze links between remarkable events noted by support staff and changes in the model's pattern. Finally, we are building a software sensor that will enable us to identify significant changes and, when necessary, raise an alert.

This article presents the methodology used, as well as the hardware and software infrastructure deployed, the measurements taken and the detection models established. It concludes with a review of the results obtained and a conclusion for future work.

2. Presentation of the experimentation in senior homes, sensors and data collected

2.1. Presentation of the experimentation

The project followed a methodological process that had already been tried and tested [25,26] by the study researchers and approved by the Toulouse Research Ethics Committee (2022-469). Some studies on the impact of data privacy on the technology adoption by older people have shown that it has a strong influence on whether they accept new technologies or not, hence the importance of understanding their attitudes to privacy policies and user agreements for these smart technologies [27]. The process began with a visit to meet the residents on the SH site to present the project and have them read and sign the information letter and consent form. Sensors are then deployed and tested. The system is installed in 14 rooms: 12 individual rooms and 2 shared spaces. A second presentation of the project's objectives was given after installation to answer residents' questions, reassure them and clear up any misunderstandings. Individual rooms have a bedroom with en-suite bathroom, both equipped with sensors. Sensors in the bedroom are mostly placed on the wall facing the bed (on the side if the room configuration does not allow it), those in the bathroom are placed on one of the adjoining walls to the door leading into the room. The shared areas include a kitchen and a living room, equipped with sensors similar to those in individual rooms. Data collection and analysis takes place over a period of 9 months (22 April 2022 - 22 January 2023) and is still ongoing. The study includes the 12 residents of the SH, who are all considered autonomous with an ADL scale of 6 [28] and IADL scale of 7.09 (± 1.38) [29]. Average age was 88. Residents sleep in the SH, except in exceptional cases (return to family, vacations, etc.). Two careers are present at the SH every day (9 am to 5 pm) to accompany residents in their activities of daily living. They report in a notebook any unusual events that they observe or that are reported to them by residents. These events may be of an individual nature (a person becoming isolated, falling, going out more often, receiving more or fewer visits...) or of a collective nature (activities within the SH such as games, shopping trip or cinema...). We assume that this information can be used to explain or validate behaviors observed by the analysis system.

The activity of a room will be addressed at two levels: first, we examine the overall activity of a room, which includes the number of daily activations of the sensors installed in each individual room compared to the activations recorded by the sensors during the same hours on previous days. We then focus on identifying specific behaviors. To do this, we build a model of sensor activity based on a sliding average, then compare different slices of the model, corresponding to a resident's average daily observable activity, using machine learning techniques applied to pattern recognition.

2.2. Technological infrastructure

The technological infrastructure was initially studied and tested in a controlled environment at the Smart Home platform¹ in Blagnac, France. The 44 sensors installed collect activity data in private and shared areas. These motion sensors are Passive InfraRed (PIR) sensors and magnetic door contacts (MC) communicating using the Z-Wave wireless protocol associated with the Domoticz² open-source home automation management software, all connected to one Raspberry Pi (RPI) per room, acting as a Z-Wave gateway. Raspberry Pis send their daily data via the local Wi-Fi (Fig. 1) to a local server connected to a secure SFTP data server located in our laboratory. Data are transmitted each night from the Raspberry Pi to the local server, and then from the local server to the lab server. In the event of a local or Internet network outage, data is backed up until the following night. We specify here that the sensors installed do not detect falls: it is the analysis of the data collected by these sensors that will.

The data was retrieved from tables and time steps were standardized using the Python language. Finally, monitoring tools for the facility have been deployed on the local server (collected system, smokeping software) to ensure that the system is operating correctly remotely, and an encrypted password-protected web portal has been developed to grant researchers an easy access to the monitoring tools and final applications (Domoticz).

2.3. Data collected

Only data from PIR motion sensors installed in bedrooms is used here. Data is collected as soon as the state of a sensor changes (Table 1). It feeds a Domoticz data file in .db format. This file is sent daily to the secure server from where it can be downloaded and analyzed. The work of querying, restructuring and data mining is done in SQL language. The activity of a room is quantified when data is received. The binary data received ("1" when the sensor detects movement in the room, immediately followed by a "0" to indicate the end of detection) is summed over 5-minute intervals (see column `capteur_1_mouv` in Table 2). The sum of the triggers describes the activity within a room for a given period of time.

Changes in the motion quantity signal will subsequently enable us to search for singular patterns that could determine a decision to launch an alert. Each individual area is identified by a random number known only by scientists in charge of the project.

3. Data processing methodology

As mentioned above, this work focuses on the study of activities in residents' bedrooms. As a reminder, we have data on activity in the bedroom, bathroom and front door of each study participant. The analysis part of the study is univariate, i.e. each room is studied separately from the others. In this article, we do not attempt

¹ <http://mi.iut-blagnac.fr>.

² <https://www.domoticz.com/wiki/Zwave>.

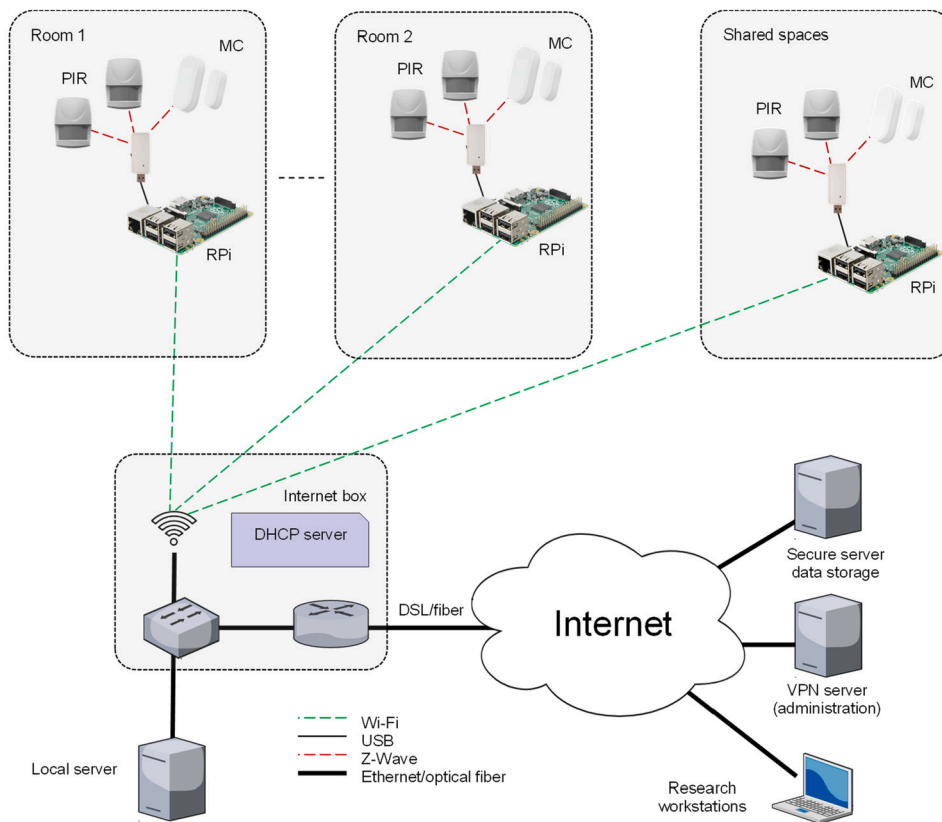


Fig. 1. Overall architecture deployed within the SH.

Table 1
Example of binary data (bedroom sensor 100_125).

DeviceRowID	nValue	Date ▼ ¹
Filtre	Filtre	Filtre
2	1	2022-11-16 18:14:26
2	0	2022-11-16 18:14:28
2	1	2022-11-16 18:21:12
2	0	2022-11-16 18:21:14
2	1	2022-11-16 18:26:53
2	0	2022-11-16 18:26:55
2	1	2022-11-16 18:27:36
2	0	2022-11-16 18:27:37
2	1	2022-11-16 18:34:10
2	0	2022-11-16 18:34:11
2	1	2022-11-16 18:39:06
2	0	2022-11-16 18:39:07
2	1	2022-11-16 18:39:15
2	0	2022-11-16 18:39:16
2	1	2022-11-16 18:39:21
2	0	2022-11-16 18:39:22

to establish links between an unusual signal in one room and activity in the other rooms at the same time. This analysis will be the subject of a forthcoming publication.

Before starting the analysis phase, it is essential to work on the structure of the data. Poor data preparation can lead to misinterpretation, slow down processing or make certain analysis impossible. Good data formatting is essential before any handling. In our

case, we need to model our data so that it is as representative as possible of resident room activity.

In this study, we are also interested in classifying our data in an unsupervised way, i.e. we have no indicator of the actual label of the signals studied. The aim of this learning process is to classify daily signals from the generated modeling of our data associated with each room into different groups. This allows to highlight one or more signals whose pattern differs from the rest of the observations. The final objective is to integrate automatic pattern recognition into the system, in order to anticipate risky events such as falls.

The aim of this section is therefore to describe the data pre-processing method, to list the various existing processing techniques and to choose the most appropriate in our case.

3.1. Data preparation

We started by pre-processing the data from the motion sensors and standardizing it. This is done in two main steps:

- Standardizing the time steps. As motion is detected as soon as the sensors are activated, standardization allows us to work with regular time intervals and eases analysis work then. To do this, we consider time slots of 30 minutes for clearer graphs, instead of 5-minute intervals used for storage in database. For each time interval, the activity value observed in the room corresponds to the sum of the motion sensor activations over that interval. For example, the time marker 9:30 is associated with the sensor readings between 9 am and 9:30 am. If the sensor is triggered 3 times during this time, the value 3 is associated with the 9:30 time slot.

This produces regularly discretized signals. For each observed day, we then have a signal divided into forty-eight 30-minute time slots, with the number of activations recorded for each slot. We assume that measurement reading errors (sensors not triggered during an activity) are negligible and equivalent for all sensors.

Table 2
Database extract after unification.

Date	capt_1_mouv	capt_2_mouv	capt_porte	capt_1_lux	capt_2_lux	capt_1_temp	capt_2_temp	capt_tv	D_piece	ID_Maison	Piece_commune	missing_value	dayofweek	weekend
Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre	Filtre
2022-11-16 18:15:00	0	0	0	24.0	0.0	23.5	23.8	N/A	125	1	Non	0.0	2	0
2022-11-16 18:20:00	1	0	0	24.0	0.0	23.5	23.8	N/A	125	1	Non	0.0	2	0
2022-11-16 18:25:00	2	0	0	24.0	0.0	23.5	23.8	N/A	125	1	Non	0.0	2	0
2022-11-16 18:30:00	1	0	0	24.0	0.0	23.5	23.8	N/A	125	1	Non	0.0	2	0
2022-11-16 18:35:00	3	0	0	24.0	0.0	23.5	23.8	N/A	125	1	Non	0.0	2	0

- Data transformation, which means converting data into a suitable format for processing. In other words, we apply data smoothing in order to reduce noise, which is achieved by averaging the data using our model. This transformation corresponds to the construction of the model described in the next section. For analysis work using machine learning techniques, we normalize our data by applying a linear scaling algorithm between the Min and Max to our parameters (MinMaxScaler of the scikit-learn python package). This allows us to work with a common scale without losing information about the overall distribution, and to optimize computation time performance. Besides, the sensitivity of machine learning techniques to the scale of the data requires this step, otherwise there is a high risk of increasing the difficulty of the pattern recognition process due to significant data variability.

3.2. Reference models

Behavior is observed through the analysis of models established for each area of the SH every day. Each model is built to detect 'abnormal' behavior by implementing different levels of detection:

1- The first level uses automatically calculated thresholds, for example based on a difference between the usual value and the value measured at a specific time slot, to highlight events that are out of the ordinary (in this case we have used the number of movement sensor triggers) as shown in Fig. 2a. Setting up this first level of detection allows us to work first on the raw data, i.e. the daily signals obtained per part, but also on the model built to highlight sudden changes.

2- The second level looks at changes in a dynamic model over longer periods of time, to highlight progressive changes as shown in Fig. 2b.

For each day d of data collection, the model is calculated by time slot as the average of observations over the previous week (day d included). This technique is very similar to the moving average process. The moving average is mainly used in time series analysis and aims to eliminate the least significant fluctuations in order to focus on long-term trends. To calculate the moving average, a time window is defined (e.g. 5 days, 10 days, etc.) and this period determines how many past values are included in the calculation of the average. This calculation is repeated by moving the time window one step. In our case, we build our model on a 7-day window. The arithmetic mean is defined in the following way

$$M_t = \frac{1}{k} \sum_{i=1}^k x_i \quad (1)$$

where k is the number of days to be considered in the window and x_i is the value recorded for the k days of observation at time t .

We have chosen to use a weighting that gives greater weight to data from the 3 last observed days. Of the 7 days used to calculate our average, a weight of 4 is assigned to day d , which is the most recent observation day, a weight of 2 to the 2 days preceding it ($d-1$, $d-2$), and a weight of 1 to the remaining 4 preceding days. We assumed that this would preserve patterns strongly correlated

with the most recent data observation, while smoothing out the incoming signal. Averages are calculated slot by slot. As the signal is divided into several time slots, there may be time shifts (e.g., a later wake-up time, etc.). However, we consider that these shifts are either small enough to be included in the 30-minute time slot and therefore no change in thresholds will be observed, or, when they are significant, are corrected by an appropriate distance metric when studying behavioral trends.

It is important to distinguish these two detection levels. The first level enables us to study strong, sudden changes that do not last over time (Fig. 2a: strong peak in activity at the beginning of the second half of the day, with no similarity to the previous day or the next day activity), while the second level is more attentive to gradual decreases or increases that will not be detectable by a quantitative threshold, as they are not large enough to give immediate warning, corresponding to a slow modification of the "usual" pattern (Fig. 2b: slight change in the intensity of model activity at the beginning of the second half of the day, due to the peak in activity shown in Fig. 2a).

The dynamic pattern is analyzed according to its shape and evolution, while the unified data is monitored by thresholds set according to the average activity observable in a room. The changes and longitudinal evolution of a resident's behavior will be studied using the dynamic model only, comparing each daily pattern with previously observed patterns. Daily signals are compared only with daily signals from previous days, just as the model is compared with patterns established for previous days. These two pieces of information are cross-checked if a change in the pattern is identified as a result of the analysis.

3.3. Processing techniques

Part of the work is based on unsupervised classification of the temporal signals collected. In this section, we give a brief overview of the relevant distances and algorithms to be applied to temporal signals. The techniques considered are among those recommended and tested in the literature.

As a reminder, our aim is to extract singular patterns in our data in order to compare new activities with previous ones. The sequences studied are daily sub sequences of the dynamic model presented in the previous section. Therefore, we work with time-dependent series, which we introduce the concept here: these are discretized signals with temporal indexing. They can be used to represent the evolution of a variable over time, highlighting components such as seasonality, i.e. a periodic phenomenon with an identified period, or the overall trend of the series, if any.

Here we present examples of:

- Classification tools: In this study, we aim to classify our data in an unsupervised way. There are many unsupervised classification methods in the literature [30]. We have chosen to present three of them before selecting one for our analyses:

1) K-means: First, we introduce the K-means partitioning algorithm, one of the most popular methods for unsupervised classification [31]. It is an iterative algorithm that classifies

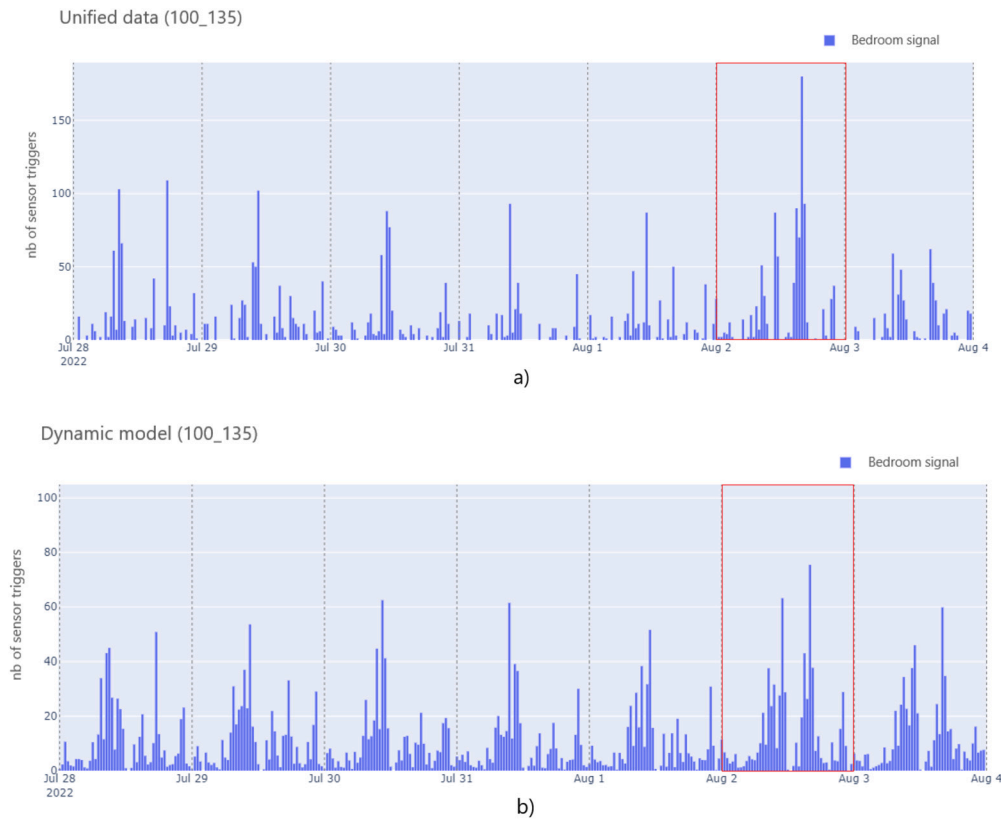


Fig. 2. Observation of a change in room activity between measured data a) and established dynamic model b) (Participant 135).

a data set into a number k of clusters, k being fixed beforehand. A similarity criterion is also set to measure the similarity between the data. This algorithm performs well on time-dependent data, for example to classify temperature in buildings [32] and is easy to set up for a first round of analysis in order to identify particular clusters.

- 2) DBScan: The DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method is particularly interesting for identifying outliers in a dataset, and, unlike K-means, does not require information on the number of partitioning classes. The algorithm takes two parameters as input: the radius of the circle created in a point's neighborhood to identify nearest neighbors, and a parameter which is the minimum number of points required in the neighborhood created to validate cluster membership. Its performance has been tested on time series [33], but the original algorithm does not seem effective on local anomalies, which could be an issue for our work.
 - 3) Hierarchical clustering: Another unsupervised clustering method is hierarchical clustering [34], which groups data into a tree-like hierarchy of clusters. It is widely used to explore and recognize patterns in datasets. It has the advantage to present the result in a dendrogram to show the distance between clusters and, like DBScan, the number of clusters is not required as a parameter.
- Distance measurements: The similarity measure plays an essential role, as it has a greater impact on classification performance than the choice of algorithm [35].

When comparing time series, there are many choices regarding the distance that determines similarity. A wise choice can significantly optimize the performance of the chosen classification algorithm. On the contrary, a poor choice of similarity criterion can mask sin-

gular patterns in the data. A comparison of different distances has been carried out on ecological time series data [36]. These include:

- 1) Euclidean distance: The Euclidean distance is the standard distance used to compare two quantities. It measures the shortest absolute distance between two points. When applied to vectors (temporal or not), it requires that the two elements being compared have the same length. Its main limitation when applied to time-dependent data is that it does not consider temporal distortions, since it requires data alignment, which implies eliminating temporal variations by compressing the series' temporal indexes.
- 2) Dynamic Time Warping distance: The DTW (Dynamic Time Warping) distance determines the minimum distance at which two time series can be aligned, taking into account non-linear time shifts. It seeks the optimal temporal alignment between two series of same or different length, using information from Euclidean distance matrix between a given point and a neighborhood of points around its Euclidean equivalent on the signal with which it is being compared. This makes it more robust in contexts such as pattern recognition, where the same events can occur at different times. Whereas Euclidean distance assumes that the points in each time series are temporally aligned, DTW is more flexible and adapts to series that may present temporal shifts by seeking non-linear alignment between two sequences.
- 3) Manhattan distance: The Manhattan Distance is used to measure the distance between two points in the form of a path. It is the shortest distance between two points on a grid, meaning that there can be one or more paths with the same distance. It is defined as the sum of the absolute differences between the coordinates of the points. Much less sensitive to extreme values than the Euclidean distance, it is often preferred for sparsely distributed data. On the other hand, like the Euclidean

Table 3
Profile of participants who suffered a fall.

Participants' ID	Age/Gender	ADL	IADL	Monitoring period	Day of event (fall)
				Bedroom	
135	96 years/F	6	7	22/04/22 – 22/01/23	12/07/22 03/01/23
205	84 years/F	6	8	22/04/22 – 05/12/23	13/11/22
232	91 years/F	6	7	22/04/22 – 22/01/23	07/06/22
250	92 years/F	6	8	22/04/22 – 22/01/23	16/05/22

distance, it cannot be used to process time series of different lengths.

Here, we discuss the choice of an appropriate algorithm and distance for processing our data.

We choose to use the K-means algorithm for a first data analysis task, as it proved to be robust for processing time series and we also valued its ease of use with the Python programming language.

Regarding the choice of an appropriate distance, we have chosen to focus on a distance that is not invariant to temporal distortions, since in the case where two signals have an identical shape but are shifted in their emission, their similarity would be low. In the context of this study, we focus on true changes in pattern shape, while recognizing that the observation of temporal shifts can be relevant information, but this is not the main objective of our analysis to detect them. Dynamic time warping seems to be the right compromise. In the remainder of this article, we will refer to dynamic time warping as DTW.

Input data have been pre-processed to optimize classifier performance: signals are split into daily windows of 24 points (one reading per hour, where the value considered is the sum of triggers recorded during this period). This windowing also enables signals to be smoothed without any loss of information. Periods when the sensors were inactive due to electronic failure are excluded from the learning process. The data is then scaled using the MinMaxScalar transformation of the sklearn.preprocessing Python library to reduce computational time costs. This transformation is detailed in Section 3.4.

3.4. Metrics

The choice of appropriate processing methods was discussed earlier in Section 3.3. The K-means algorithm is described by the following expression:

Within a cluster, the aim is to minimize intra-cluster variance, i.e. each observation is assigned to a cluster center under the following condition:

$$\arg \min_{c_i \in C} d(c_i, x)^2 \quad (2)$$

where C is the set of k centers; x is the observation; d is the distance between the cluster center and observation x ; and we try to meet the minimization criterion:

$$\min \sum_{i=1}^k \sum_j d(c_i, x_{ij})^2 \quad (3)$$

where x_{ij} is the j -th observation in the cluster whose center is c_i .

As mentioned above, the number k of clusters is fixed. It is determined by the “elbow-method”, which aims to evaluate the average of the squared distances of the respective cluster centers for several values of k and to determine the inflection threshold at which this value no longer decreases significantly [37].

The KelbowVisualiser function in the yellowbrick.cluster python library is used to determine k .

The similarity criterion selected is the DTW, which allows temporal shifts to be considered. It compares two sequences by minimizing the sum of amplitude differences, while allowing for stretching or compression over time. Mathematically, the DTW distance is calculated by solving the following optimization problem:

$$d_{DTW}(X, Y) = \min_{w \in W} \left(\sum_{(i,j) \in w} (X_i - Y_j)^2 \right) \quad (4)$$

where W is the set of possible alignment paths between X and Y .

4. Results

This section presents the main results obtained using the metrics described above. To illustrate our results, we choose to present as an example the results of observation only in the context of four significant falls that occurred at the SH at different times and for different residents. We will present qualitative observations, starting with the processing of raw data, focusing on the first level of detection (thresholds), then on the model by qualifying the progressive changes observed. Then, a more quantitative approach will be presented, with the results of the classification of our representative models using K-means to extract any singular patterns.

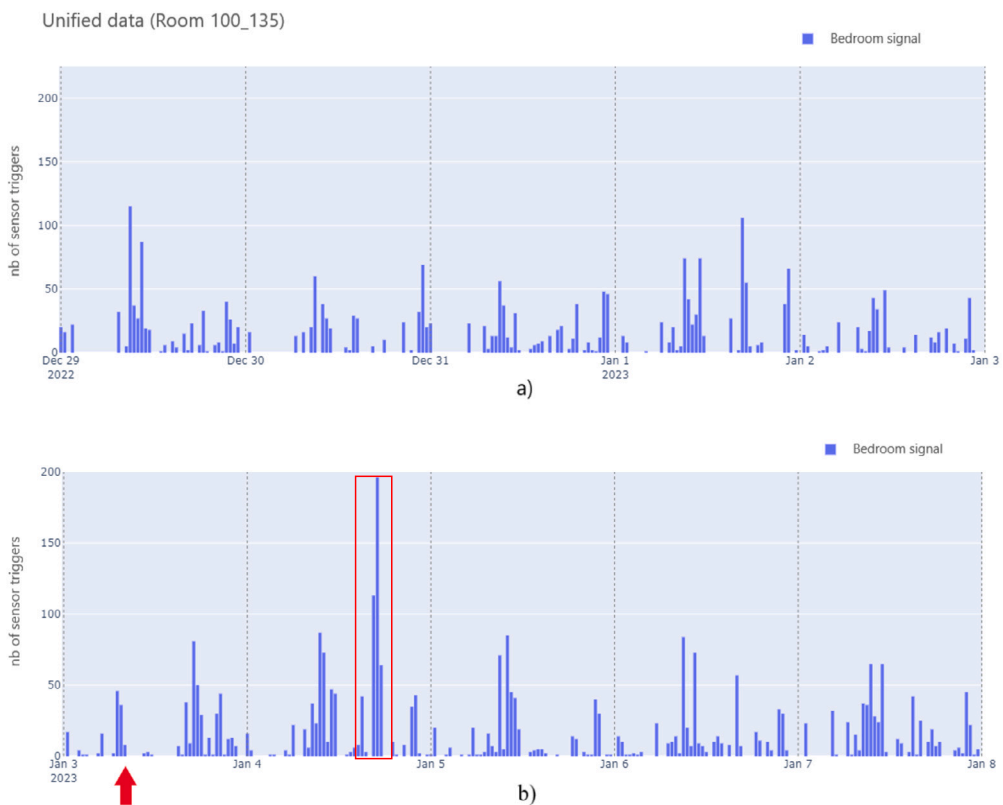
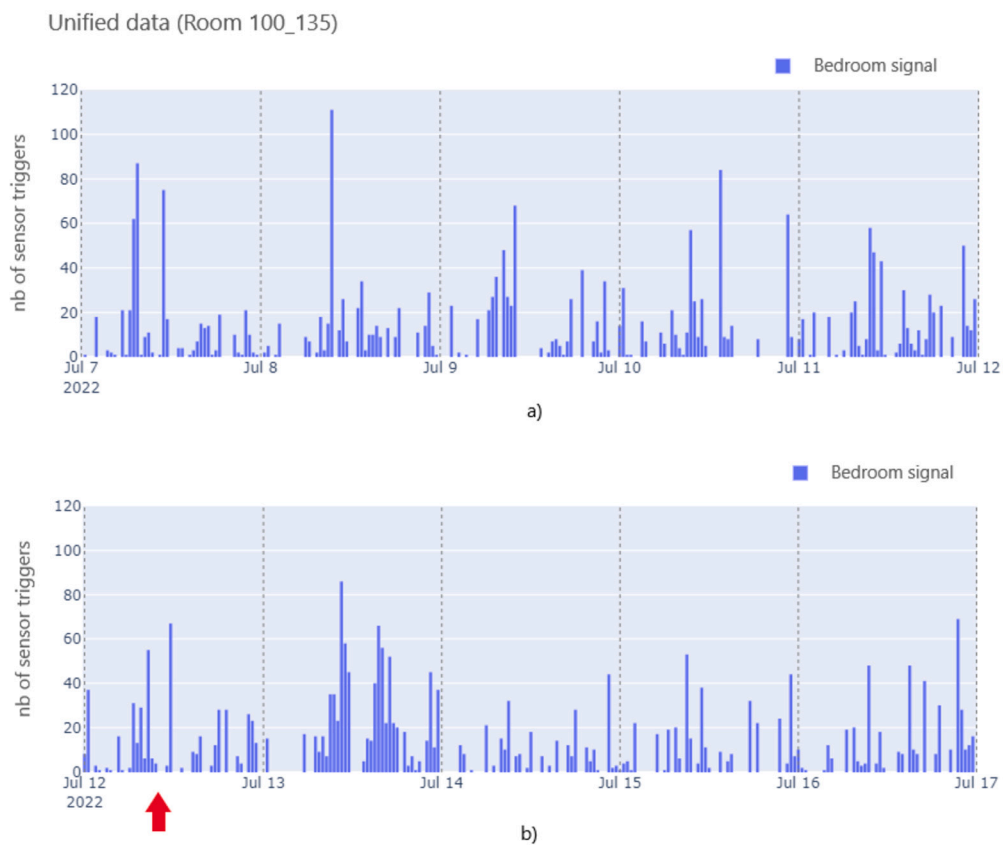
4.1. Observation of activity

During the observation period, SH staff noticed 4 falls, involving 4 of the house's occupants.

Their profiles are listed in Table 3. These 4 autonomous people (ADL=6 and IADL between 7 and 8) have fallen at least 1 time. However, in this article, we present the observations of 4 falls which show different behaviors depending on residents when they return to the SH, and on whether or not they have been hospitalized. The comparison between days is made by matching each time slot from one day to another, with each day uniformly divided into 30-minute intervals.

Fig. 3 illustrates an example of motion readings from the sensor installed in the bedroom of the participant 135, before (3a) and after (3b) the first fall of the resident on July 12, 2022 in the late morning. Time of the fall is indicated by a red arrow. The day after the fall (July 13), the signal is denser than the other days. Indeed, the number of triggers is significantly higher for almost every 30-minute window of the day, probably due to visits from other residents, SH staff, family and/or medical assistance following the fall. For the following days, it is however difficult to say something just by looking at the signal. We can't deduce anything about the pattern and the activity rate is quite similar to what was observable on previous days.

Fig. 4 shows an example of motion readings of participant 135, before (4a) and after (4b) the participants' second fall in the morning of January 3, 2023. The number of triggers is usually rather low. However, as in the first example, there was a high level of activity the following afternoon, as for Fig. 3, we assume that it is due to extra care from other participants and the SH's staff, and



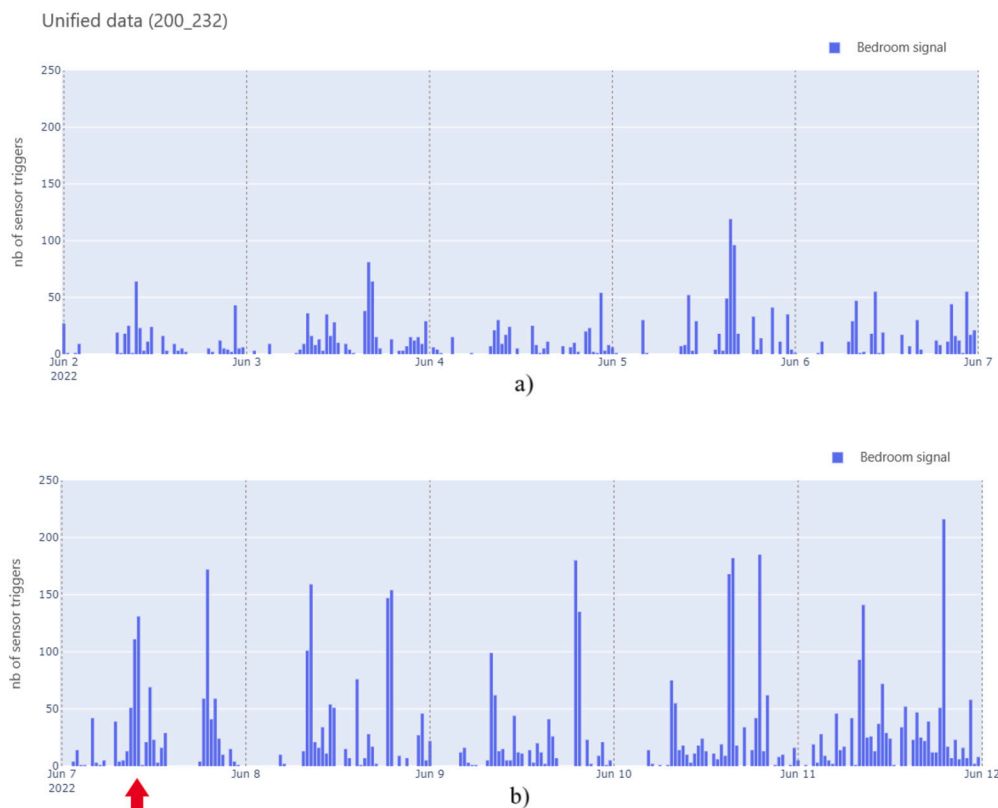


Fig. 5. Unified data before a) and after b) a fall event (Participant 232).

then a return to an activity rate similar to what we could observe before the event.

The third example in Fig. 5 shows the activity of participant 232 over the period of June 2 to June 11, 2022, with a fall recorded on June 7. We see a clear increase in the number of movements in the morning and evening after the fall due to the assistance provided in getting up and going to bed, where activity was relatively low before the event. In this particular case, a significant change can be observed in the raw activity behavior data.

In Fig. 6, we look at another example of movement records in participant 250's room around the date of the fall (May 16, 2022 in the morning). Here, it is difficult to identify a change in the amount of activity. We also note that the resident was absent from the SH from May 12 (evening) to May 15 (evening) because she had to return to her family for vacation, which explains the high concentration of activity on the morning of May 12 (preparation for departure: observable for all residents before an absence from the SH over several days).

These first results indicate that it is difficult to interpret raw data directly from the sensors, especially if the analysis is carried out without information on the individual's lifestyle and the events that may affect it. Nevertheless, this first step remains relevant when it comes to threshold detection.

In this work, we have used these a posteriori annotations to correlate real information with observations obtained from sensor data and give them meaning.

In the context of automatic detection, obtaining these annotations is essential during the model learning stage.

We recognize here that reading activity as it stands is difficult, and does not consider possible time shifts: for example, if a resident's wake-up time is delayed, the activity following wake-up may be postponed and/or amplified to the next time slot, without this being alarming.

However, this initial analysis can be used to detect excessive activity compared with other days in the same time slot, and can later be combined with other results to formulate hypotheses.

4.2. Observation of model behavior

We recall here that by observing the dynamic model, we are interested in the change in form of the signal over time. We study the four cases of falls really recorded at the SH.

Fig. 7 and Fig. 8 show the bedroom model of participant 135, who fell twice during the study: the first fall took place on July 12, 2022 in the late morning in the resident's room, and the second on January 3, 2023, also in the room, around 8 am. In all the figures presented in this section, the time of fall is indicated by a red arrow. We have also visually estimated the average peak activity over the study period. This estimate is represented by the dotted black line in Figs. 9 to 10. The black downward and upward arrows indicate respectively a decreasing and increasing trend in activity over the period studied. It should be noted that the black elements represent a qualitative and not a quantitative assessment, intended to make the reading of the graphs.

Observation of the pattern following the first fall does not appear to result in any increase or decrease in activity in the room. The shape of the signal also remains similar to what was observable before the event, with the same three notable hotspots of activity each day (mid/late morning, mid-afternoon and late evening).

Fig. 10 shows the dynamic model of participant 135, where we observe the same significant increase of activity as Fig. 3 (unified data) in the afternoon of the day after the fall. We can also see that activity in the late morning following the fall is lower than that observed on the preceding and following days. Except for these singularities, model activity is similar before and after the fall, with the same moments of activity as for the first fall. We can therefore

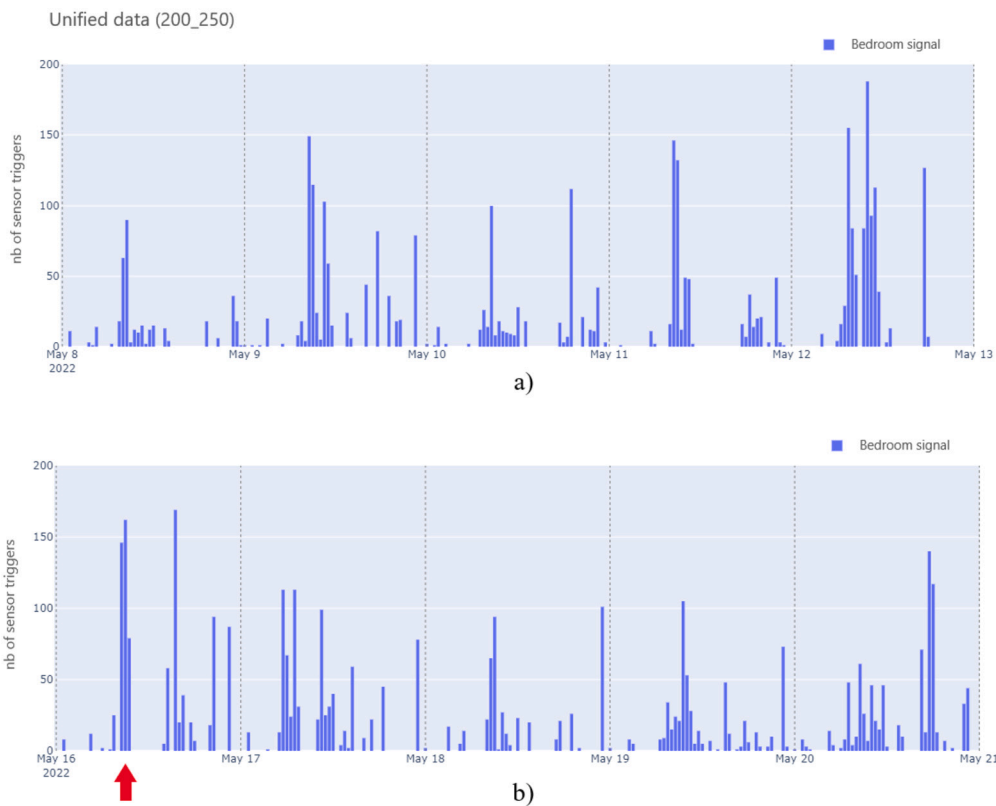


Fig. 6. Unified data before a) and after b) a fall event (Participant 250).

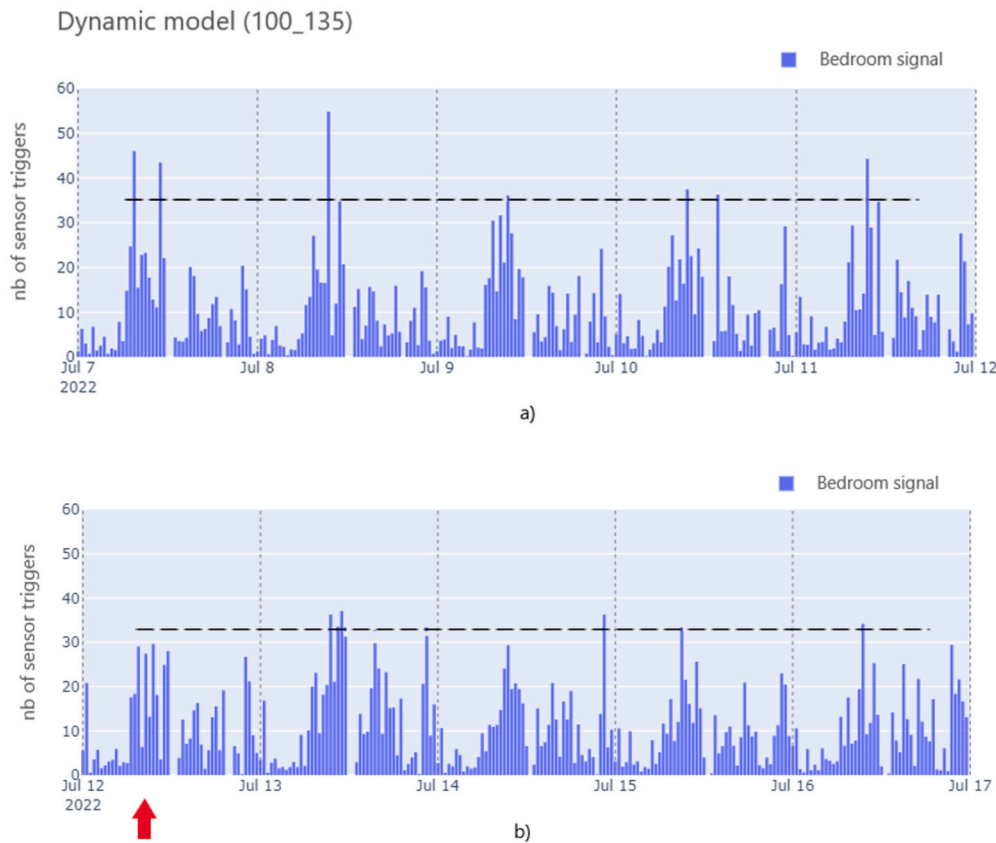


Fig. 7. Dynamic model before a) and after b) the fall (Participant 135).

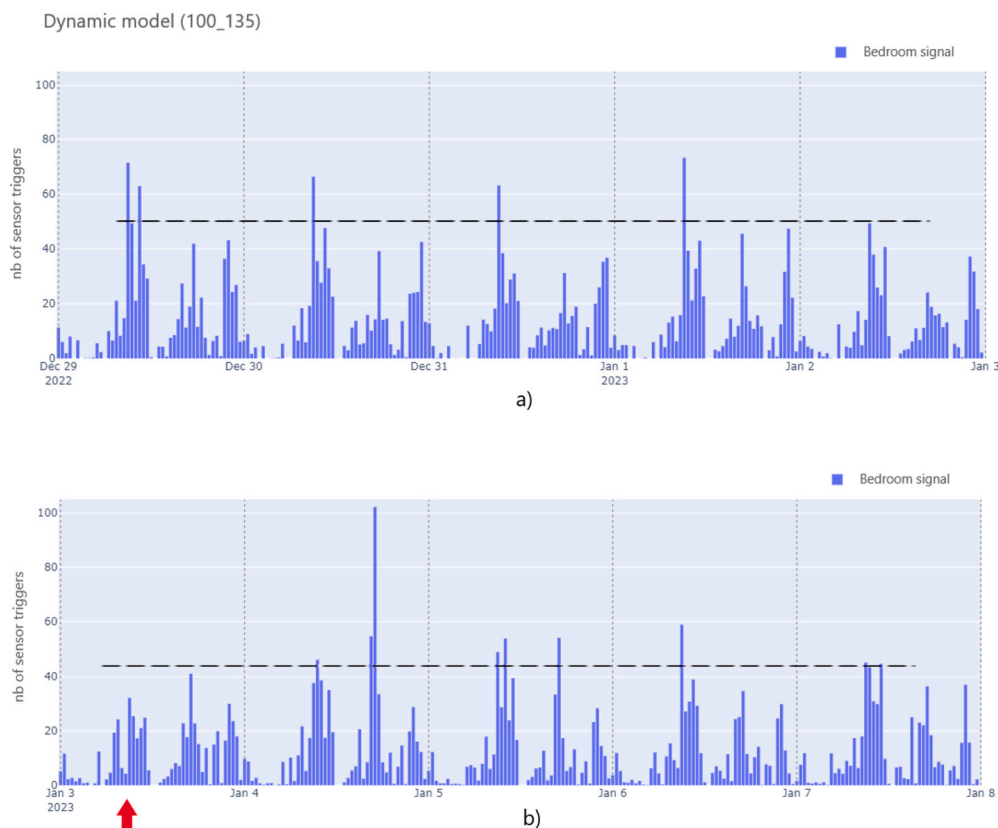


Fig. 8. Dynamic model before a) and after b) the fall (Participant 135).

consider that the event had no effect on the participant's mobility or habits, as attested by the observation notebook, which also indicates that, as for the first fall, the participant was not hospitalized.

Fig. 9 presents the dynamic model in participant 232's bedroom before and after the fall on the morning of June 7, 2022.

We immediately observe a sharp increase in activity in the room, in particular two peaks in the morning and evening and sometimes in mid-afternoon. The participant broke her wrist and was taken care of at the time of the fall (no prolonged departure of the SH). According to the observation notebook, she receives outside help when she gets up and goes to bed, which would explain the increase in morning and evening activity. This new high level of activity in the bedroom ended around September 10. We are not aware of the end date of external aid for the participant. Nevertheless, the activity in Fig. 10c over the week remains higher than before the fall. Also, for this event, the changes are more remarkable in amplitude than in form: indeed, the periods when activity is concentrated in the room before and after the fall remain the same.

Fig. 10 illustrates the dynamic model of the participant who fell on May 16, 2022 (Fig. 10b). She then stayed in the SH for two weeks before being hospitalized on June 3, 2022 for a pelvic fracture. She returned to the SH on June 20, 2022. We note that changes in the model are significant as early as the day after the fall, both in the intensity of movements (amplitude < 50%) than in the abnormally irregular shape of the signal. In particular, the strong morning activity observed prior to the event is nowhere to be seen. This may indicate a difficulty moving. In the bedroom, there is also a low-intensity, regular activity in the afternoon, which was not observed prior to the resident's fall. The pattern of the days following her return to SH (Fig. 10c) shows a

return to regular activity, but different from before the fall, with a lower morning intensity spread out over the day.

Several days after her return, the model gradually returned to values in line with its usual pre-fall behavior, both in terms of intensity and signal pattern (Fig. 10d).

The analysis of the other falls nevertheless confirms the fact that monitoring the evolution of the dynamic model is much more relevant than monitoring daily data, which is noisier and more sensitive to external events (various activities in the shared house, etc.), and can therefore potentially cause false detections and interpretations.

Finally, following the observation of our models, we are able to define a causal link between the fall event and the impact on a resident's habits only through the pattern and intensity of his movements in his assigned room. There are several consequences in the different cases studied:

- No change i.e. no characteristic difference between what is observable before and after the fall (case of participant 135 for both fall events);
- Change in the quantity of movements recorded but not in the form of the signal: case of participant 232 who received external help in her room, hence the increase;
- Change in the amount of motion recorded and in the shape of the signal (case of participant 250): immediate change in the resident's pattern, if the signal is irregular in the days following the event, we know that the participant is having difficulty moving around.

Another observation is that the dimension of the fall event is rather large: we cannot distinguish sudden and accidental falls from falls induced by a progressive deterioration in a resident's condition. For the four fall cases presented, through the observa-

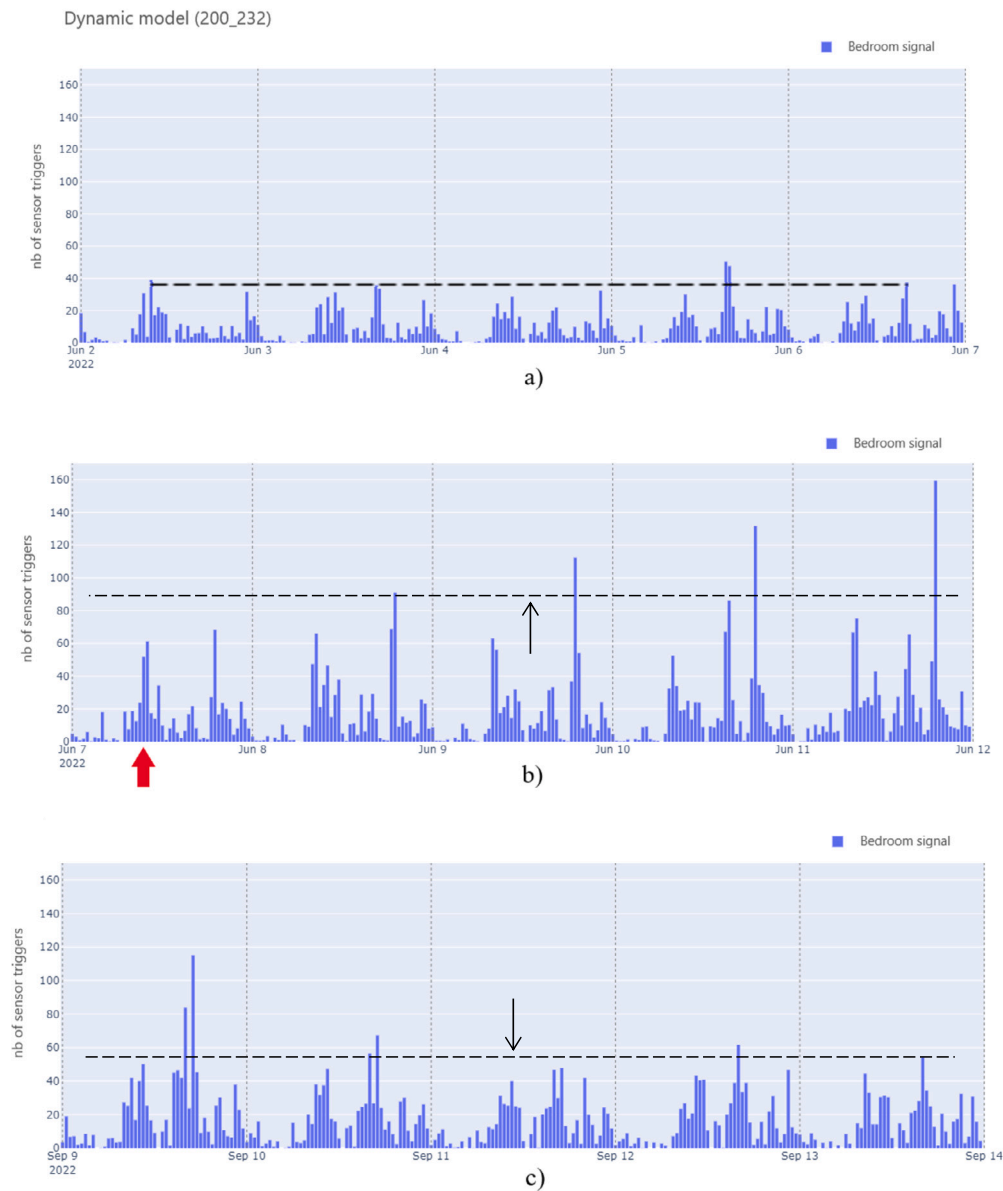


Fig. 9. Model evolution (Participant 232) before the fall (a), after the fall (b) and back to before the fall (c).

tion of dynamic models, we are unable at this stage to determine whether these falls are accidental or induced. However, the use of machine learning will enable us to identify patterns in the prediction of an abnormal event that could lead to a possible fall.

4.3. Clustering results

The choice of the number of classes $k=6$ for data partitioning presented in Fig. 12 (participant 250) is made with the result displayed in Fig. 11. The different classes returned by the algorithm are presented, with the assigned signals for each cluster in gray and the barycenter (average of the partitioned signals within the same cluster) in red. Fig. 13 shows the number of signals classified in each of the 6 clusters.

Clusters 1, 2 and 3 (Fig. 12) share similarities in form, while the other three groups are more singular: in cluster 0 are classified the series from May 24 to May 31. We remind here that participant 250 fell in her bedroom on the morning of May 16. Looking at the distribution of signals within clusters, we see that the sequences of her dynamic model between the time of the fall and her departure from the SH for hospitalization (June 3) are essentially distributed

within clusters 0 (4 dates), 3 (4 dates) and 5 (9 dates). The fact that signals are distributed in different clusters may be due to noise in the data. In addition, the K-Means algorithm forces the allocation of a signal within one of the 6 defined clusters, which can lead to random assignments if a signal is significantly different. It will be assigned to the most similar cluster, but if it is an outlier, the assignment may be incorrect. Also, in the dynamic model, changes may be gradual, given the way the model is built.

Fig. 14 shows the classification results for another room of the SH (participant 232), and Fig. 15 the distribution within the 6 established clusters. Clusters 0, 3 and 5 are among the classes with the fewest signals affected, which are indicative of the singularity of the shape, without admitting whether or not it is abnormal.

Clusters 0, 2 and 5 (Fig. 14) present strong similarities: in red, barycenter have the same pattern. Cluster 1 is characteristic of the absence of model activity during periods when the resident is not at the SH.

Within cluster 3, we find the model daily signals following the fall of the participant on June 7, 2022. The signals classified in this cluster correspond to the continuous period between June 7 and

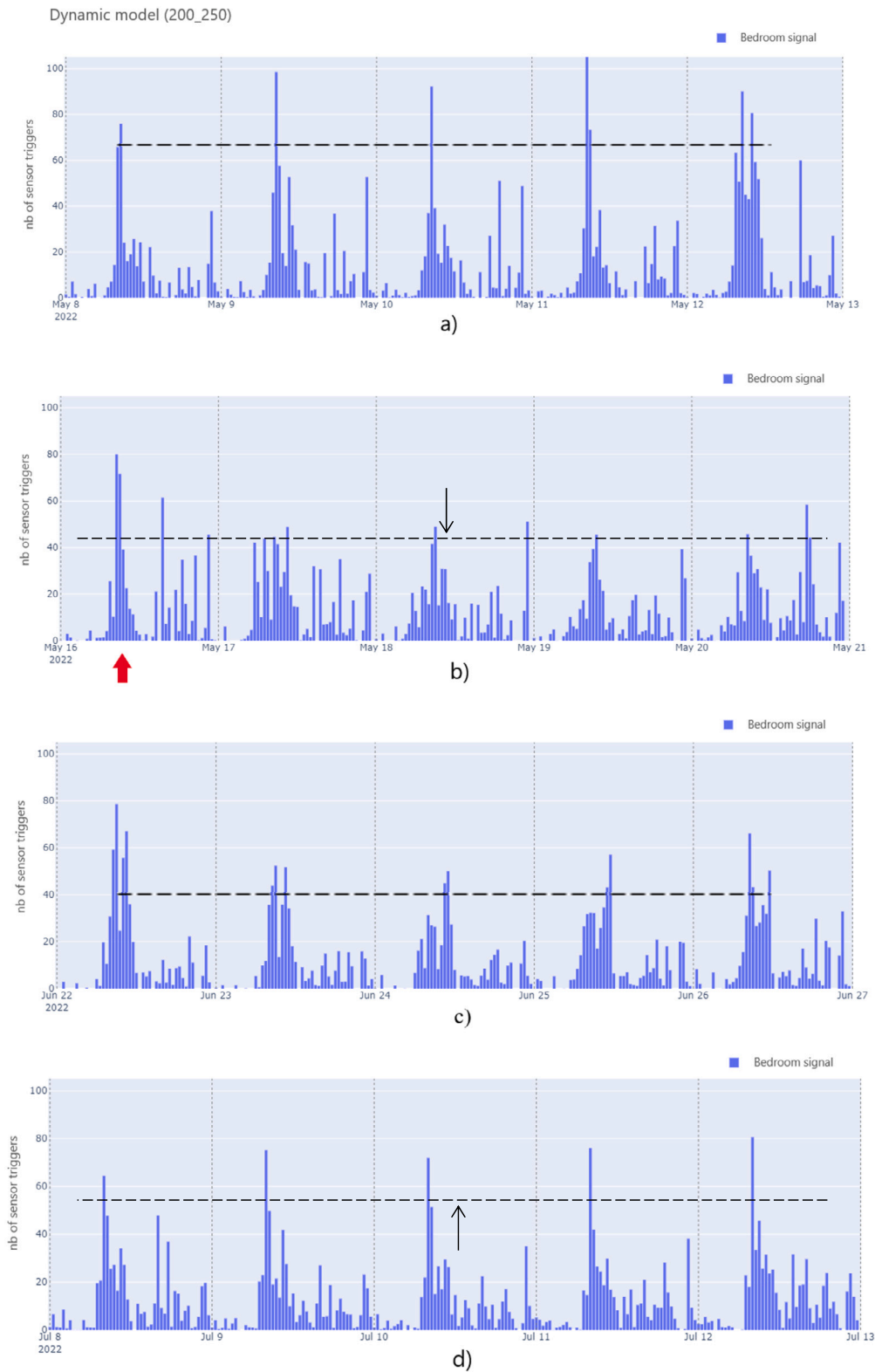


Fig. 10. Evolution of the dynamic model (Participant 250), before the fall (a), after the fall and before hospitalisation (b), return from hospitalisation (c) and return to normal behavior (d).

July 21, with a few exceptions. The last cluster (4) is atypical, but the entries associated do not follow each other in time, i.e. there is no reproducibility of the signal over several days in a row.

Through these results, we can say that the reliability of the clustering for this method depends strongly on the regularity and periodicity observable in our input signals: the more regular they

are, the more uniform the groups are and therefore the more relevant the interpretation seems to be.

Then, we can correlate the results of data partitioning with the information shared by careers living with residents. Two cases challenge our interpretation: A/ singular patterns highlighted by the clustering do indeed correspond to a period when the partic-

Table 4
Pros and cons of the K-means and DBSCAN methods

	Pros	Cons
K-means	Similarity criterion adapted to time distortion (DTW)	Predefined number of classes: singular signals may be assigned to a cluster with signals that we consider usual
DBSCAN	Does not force assignment: handles outliers	Can't define relevant classes: tends to identify most entries as outliers

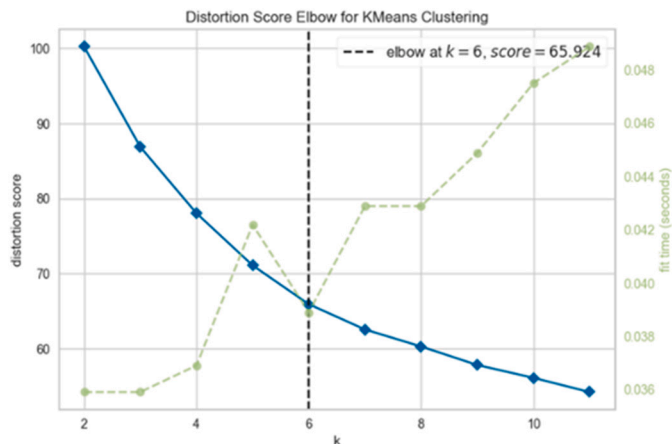


Fig. 11. Distortion score using data from Participant 250's bedroom.

ipant changed his habits due to mobility difficulties following an event, but they can be classified within a class with patterns that can be described as normal (i.e. which do not represent abnormal behavior); B/ singular patterns are scattered across different groups (i.e. we don't observe signals that follow one another over time within our classes), and as a result, interpretation and pattern identification fail.

Other limits to this partitioning method were noted: for several runs of the algorithm, the allocation of some signals to a cluster may change due to the still significant presence of noise in the input signals. Even if K-means algorithm is considered robust on noisy data, the pre-processing of the data, in particular its denoising is questionable: how can we smooth a signal without losing too much essential information? When studying medical data, it is crucial to ensure that the processing is thorough, and in our case, that the results are correctly interpreted in order to avoid missing information that could have an impact on the patient's health.

Other unsupervised partitioning algorithms have been considered and tested, without providing results as convincing as the K-means method. DBSCAN method, as seen earlier, is particularly interesting for identifying outliers in a dataset, and does not require information on the number of partitioning classes. For the purposes of this study, the algorithm proved inefficient, as it tended to group almost all entries as outliers. By studying the structure of the data, we have established that density-based clustering is not adapted to the distribution of the inputs, which are certainly too noisy and therefore affect the performance of the algorithm. A summary of the pros and cons of these two methods is provided in Table 4.

Considering the results, the K-means algorithm is quite efficient on our input data, but we also note that data pre-processing is very important when applying classification algorithms: a signal that is too noisy can be difficult to interpret, while one that is too smooth can potentially lose the information needed to validate the relevance of a model. K-means offers a relevant classification for a first phase of analysis, with links between fall events and the different groups formed by the algorithm.

5. Discussion

A number of limitations are highlighted at the end of this initial analysis phase. First of all, the consideration of time shifts in the study of our data can be discussed: indeed, if we assume that the intensity of activity, and therefore the model, does not change shape but shifts over time, we will need to be able to distinguish a significant and characteristic time shift indicative of a change in habits, from a random shift. This underlines the importance of correlation with SH carers' data to be able to supervise part of the learning process.

Regarding fall prediction and detection, the current model mainly observes whether a fall has affected a resident's habits. For the next phase, we recommend analyzing the data by distinguishing between daytime and night-time activity, for a more detailed understanding. This distinction will also help to differentiate times when SH carers are present from those when residents are alone and thus more vulnerable. Indeed, the daytime signal may be disturbed and less robust, as the activity associated with a resident during the day does not distinguish between outside visits and the resident's individual activity. The night-time signal appears to be more regular and stable. Moreover, the detection of falls occurring during the day seems less necessary, since carers are present to take care and report the fall.

Falls prediction is currently difficult to establish due to the constraints highlighted above (time shift, disrupted diurnal signal): by studying the days preceding the observed falls, we have not yet been able to clearly identify a change that could have prevented the event. We recommend making a distinction between two types of falls: falls resulting from a deterioration in the resident's condition, which should be detectable thanks to more advanced classification and pattern recognition work still in progress, and accidental falls, which are not predictable but should be detectable thanks to the introduction of thresholds.

6. Conclusion

After developing and validating the technological infrastructure in a controlled environment, we deployed it in a real-life environment in a house shared by 12 residents. Several sensors were installed, including 2 PIR motion sensors per room and 1 door contact sensor. This article focuses on fall events analysis. The data collected over 9 months enabled us to model the usual behavior of each resident and show notable changes in activity patterns after special events like falls. Detection was validated by the SH carers' annotations, acting as a ground truth, on the days when the falls occurred.

In this study, by observing the movement signals of residents who fell during the course of the study, we were able to identify characteristic post-fall behaviors (falls without consequences, falls with difficult recovery, etc.) that enable us to better understand residents' mobility. Classification work provides a better understanding of the data and has highlighted patterns that are unusual for residents. The use of detection thresholds to compare quantities of movement is complementary to work with Machine Learning techniques, which can next be used for intelligent detection of high-risk events (predictive work).

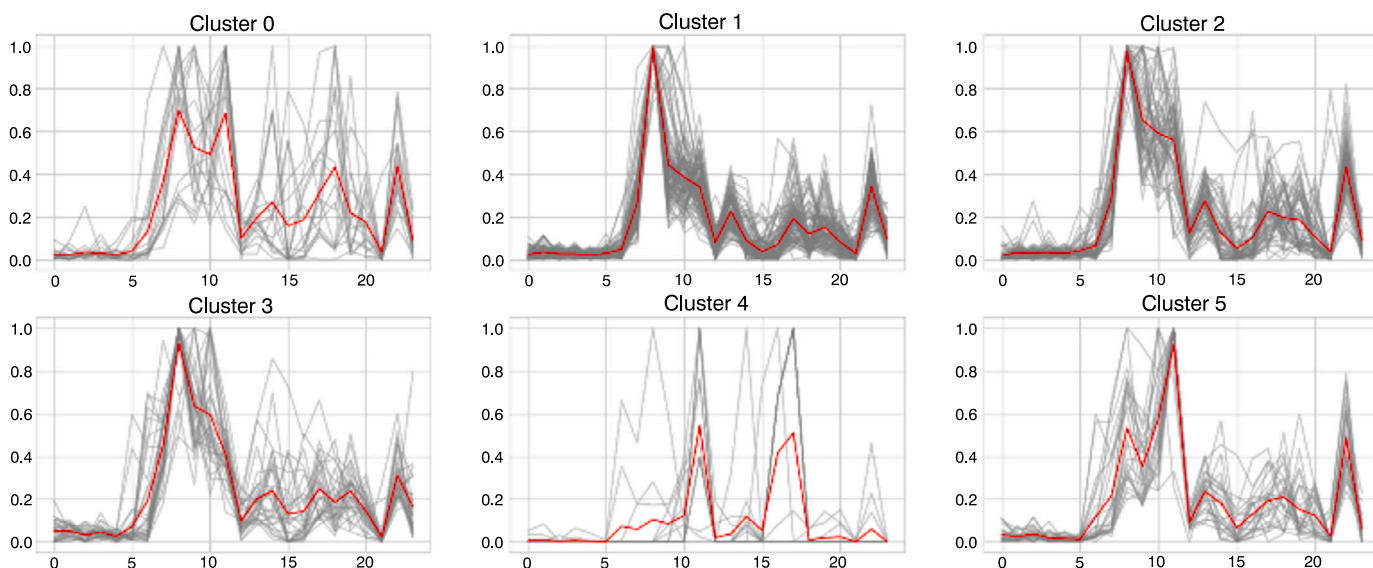


Fig. 12. Results of dynamic model sub sequences classification (Bedroom participant 250) using DTW metric K-means algorithm.

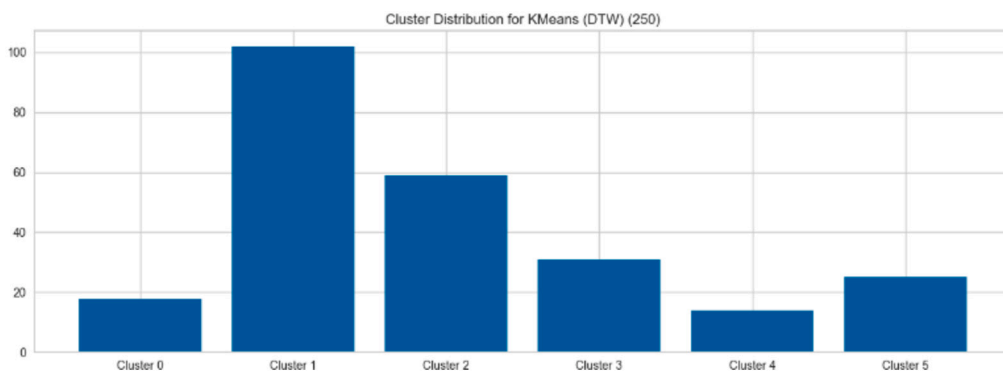


Fig. 13. Signal distribution by cluster (Bedroom participant 250).

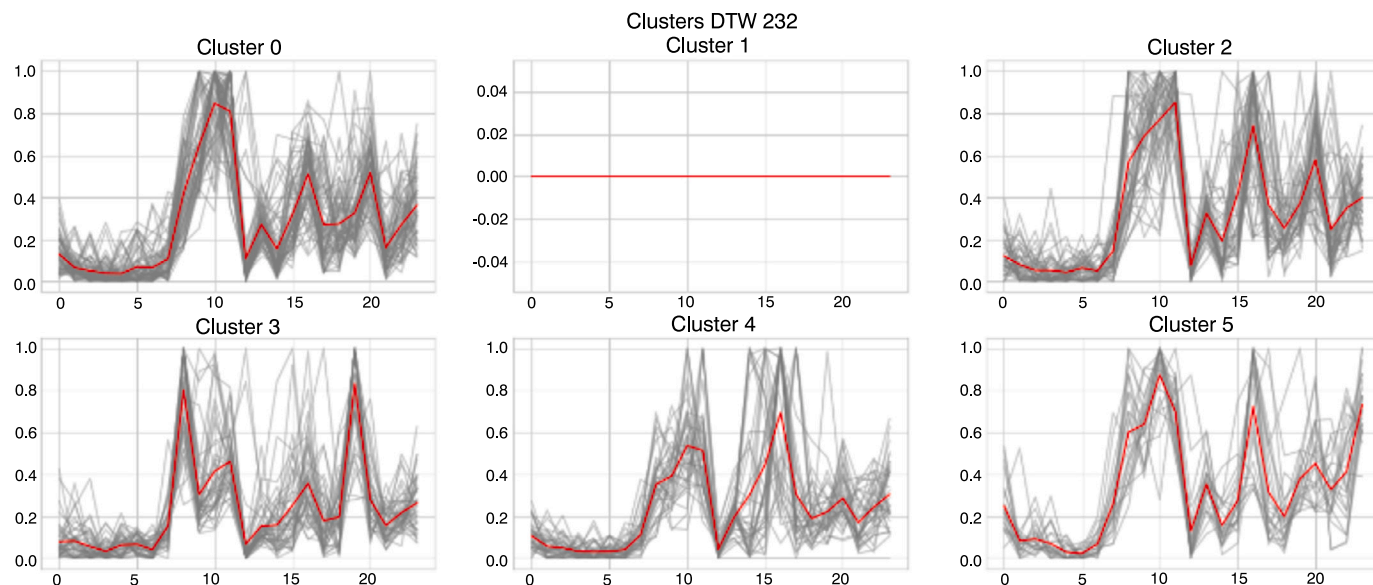


Fig. 14. Results of dynamic model sub sequences classification (Bedroom participant 232) (DTW metric K-means algorithm).



Fig. 15. Signal distribution by cluster (Bedroom participant 232).

Therefore, current work involves using K-means and testing other unsupervised classification algorithms to automatically identify deviations in amplitude or rhythm, this time to predict the risk of events. The sensors we use also provide data on luminosity and temperature, which we intend to use to analyze changes in behavior and reinforce this prediction.

The next step will be to deepen this validation with “field” annotations, and to develop an autonomous system capable, based on supervised learning of a resident’s behavior patterns, of detecting changes or, better still, predicting them.

CRedit authorship contribution statement

Laura Maligne: Writing – review & editing, Writing – original draft, Software, Formal analysis. **Eric Campo:** Writing – review & editing, Writing – original draft, Supervision, Project administration. **Adrien van den Bossche:** Resources. **Nadine Vigouroux:** Methodology, Conceptualization. **Frédéric Vella:** Conceptualization. **Olivier Negro:** Resources. **Dan Istrate:** Resources, Conceptualization. **Vincent Zalc:** Resources, Conceptualization. **Pierre Rumeau:** Resources, Methodology, Funding acquisition, Conceptualization.

Author contributions

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship. Individual author contributions are as follows:

Laura Maligne and Eric Campo are the principal editors of the article. Eric Campo was in charge of the study and followed the technical instrumentation. Laura Maligne carried out the data processing and analysis. Adrien van den Bossche and Olivier Negro played an active role in sensor and network deployment at the experimental site. Nadine Vigouroux and Pierre Rumeau conducted interviews with study participants at two points during the experimentation. Frédéric Vella participated in the design of a technical part in living lab. Dan Istrate and Vincent Zalc helped design the hardware infrastructure and set up the data server.

All the authors made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work. All of them have reviewed the paper and bring some corrections. All of them have approved the version submitted.

Informed consent and patient details

The authors declare that they obtained a written informed consent from the patients and/or volunteers included in the article and that this report does not contain any personal information that could lead to their identification.

Human and animal rights

The authors declare that the work described has been carried out in accordance with the Declaration of Helsinki of the World Medical Association revised in 2013 for experiments involving humans as well as in accordance with the EU Directive 2010/63/EU for animal experiments.

Funding

This work has been partially supported by the ASF organisation for the funding of the equipment and by Toulouse University Hospital for an internship grant.

Declaration of competing interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

Acknowledgements

The authors would like to express their gratitude to the ASF organization for funding the equipment, to the residents and careers of the SH in Brens, France (81) for their participation in the project, and to the Toulouse University Hospital for co-funding the study.

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