CONNECARE

WP4 – SELF-MANAGEMENT AND MONITORING

D4.4: ASSISTIVE MONITORING TOOLS

H2020-EU.3.1: Personalised Connected Care for Complex Chronic Patients

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Abstract	This deliverable summarizes the work done regarding the assistive monitoring tools. In particular, due to the requirements from the project during its very beginning, Eurecat took the decision to use a data simulator instead of the sensor-based system decided at the beginning. This deliverable presents a proof of concept related to the fusion of domotic and environmental data with those from the SMS (in particular, the wristband).

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Executive Summary

In the initial plan of the project, as reported in the Document of Actions of CONNECARE, the assistive monitoring tools were conceived for patients that need special and continuous assistance. The idea was to rely to eKauri, a system composed of domotics and environmental sensors installed at a patient's home. Starting from the data gathered from the sensors, the assistive monitoring tools in CONNECARE were thought to study indoors habits.

When this solution was presented during the kick-off meeting of the project in Barcelona, clinical partners expressed the difficulties of installing a sensor-based system at patients' home. In fact, due to the nature of the planned implementation studies and the followed real-world approach, clinical partners from all the four CONNECARE sites agreed that installing domotics and environmental sensors at the patient's home was out of the scope of the selected case studies.

Due to the impossibility to install any kind of environmental sensors at patients' home, EURECAT decided to adopt a software component explicitly designed to simulate sensor data for testing and data analytics purposes. This tool is capable of producing single or repetitive measures over time, depending on statistical models, configured via parameters. It simulates measures like in a real scenario with a default ordinary behavior, with a probability of changing it to a certain degree, or produce data replicating preconfigured unexpected behavior. This allows the simulation and testing of the standard operational mode of the project, and it will also be able to reproduce abnormalities that should be automatically detected by intelligent algorithms or sets of rules.

This deliverable briefly illustrates the original selected system (namely, eKauri), the adopted virtual living lab, and illustrates how domotics and environment sensors may be used in conjunction with the CONNECARE system (especially, the SMS) to provide a better follow-up of the patients at their home.

The following deliverables are recommended to be read, in order to have the overall view of the Self-Management System. Nevertheless, due to the nature of this task, this deliverable is stand-alone.

Number	Title	Description
D4.1	First self-management system	This document describes the first version of the self-management system (SMS) as a study release to be used during the clinical studies by the patients. The document presents the architecture, development phases and deployment of the system, and the requirements requested by the patients and professionals.
D4.2	Basic monitoring tools	This deliverable illustrates the tools (services) that have been investigated and developed to be part of the SMS in order to perform monitoring of basic activities. The underlying model, that will be common also for the advanced

		and assistive tools, has been first introduced in order to give the big picture of how monitoring is performed in CONNECARE. Each implemented service has been then described at a high-level, whereas in the annexes technical details of each are given.
D4.3	Advanced monitoring tools	This deliverable illustrates the tools (services) that have been investigated and developed to be part of the SMS in order to perform monitoring of advanced activities. The underlying model, common for the basic tools, has been already introduced in D4.2. Each implemented service has been then described at a high-level, whereas in the annexes technical details of each are given.

1. eKauri at a Glance

To the original idea and the potentiality of assistive monitoring for people in needs into context, such as the CONNECARE patients, we briefly summarize the eKauri system[1]. The interested reader is referred to [1], [2], and [3] for more information.

1.1 The Sensor-based Telemonitoring and Home Support System

To monitor users' activities, Eurecat developed a sensor-based telemonitoring and home support system (namely, eKauri) able to monitor the evolution of the user's daily life activity.

The implemented system is able to monitor indoor activities, relying on a set of home automation sensors and outdoor activities by using Moves[2]. Information gathered by eKauri is also used to provide context-awareness relying on ambient intelligence [4]. Monitoring users' activities through the eKauri also gives us the possibility to automatically assess quality of life of people [5].

The high-level architecture of eKauri is depicted in Figure 1. As shown, its main components are: home; healthcare center; middleware; and intelligent monitoring system.

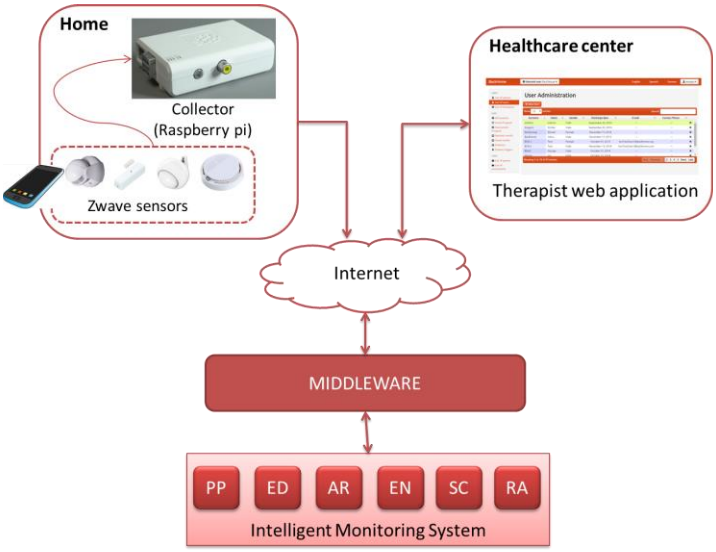

Figure 1 - Main components of eKauri.

At home, a set of sensors are installed. In particular, we used presence sensors (i.e., Everspring SP103), to identify the room where the user is located (one sensor for each monitored room); a door sensor (i.e., Vision ZD 2012), to detect when the user enters or exits the premises; electrical power meters and

[1] https://www.ekauri.com/?lang=en

[2] http://www.moves-app.com/

switches, to control leisure activities (e.g., television and pc); and pressure mats (i.e., bed and seat sensors) to measure the time spent in bed (wheelchair).

The system is also composed of a network of environmental sensors that measures and monitors environmental variables like temperature, but also potentially dangerous events like gas leak, fire, CO escape and presence of intruders. All the adopted sensors are wireless z-wave[3]. The sensors send the retrieved data to a collector (based on Raspberry pi[4]). The Raspberry pi collects all the retrieved data and securely redirects them to the cloud where they will be stored, processed, mined, and analyzed. The proposed solution relies on z-wave technology for its efficiency, portability, interoperability, and commercial availability. In fact, on the contrary of other wireless solutions (e.g., ZigBee), z-wave sensors are able to communicate with any z-wave device. Moreover, we adopted a solution based on Raspberry pi because it is easy-to-use, cheap, and scalable.

In specific case studies, we also use the user's smartphone as a sensor by relying on Moves, an app for smartphones able to recognize physical activities and movements by transportation. Among the activity trackers currently on the market, we selected Moves because it does not need active users' interventions[5].

The professional interacts with the overall system through a suitable interface aware of end-user needs and preferences.

The middleware, which acts as a SaaS, is composed by a secure communication and authentication module; API module to enable the collector transmitting all the data from sensors to make them available to the intelligent monitoring system; and further utilities such as load balancing and concurrency.

In order to cope with the data necessities of the actors of the system (i.e., therapists, caregivers, relatives, and end-users themselves), an Intelligent Monitoring system has been designed. It is aimed to continuously analyze and mine the data through 4-dimensions: detection of emergencies, activity recognition, event notifications, and summary extraction.

In order to cope with these objectives, the Intelligent Monitoring system is composed of the following modules (see Figure 2): PP, the pre-processing module to encode the data for the analysis; ED, the emergency detection module to notify, for instance, in case of smoke and gas leakage; AR, the activity recognition module to identify the location, position, activity- and sleeping-status of the user; EN, the event notification module to inform when a new event has been detected; SC, the summary computation

[3] http://www.z-wave.com/

[4] http://www.raspberrypi.org/

[5] The Moves app stopped on July 2018. It is worth noting that in the case of CONNECARE the idea was to change Moves with the CONNECARE SMS.

module to perform summaries from the data and to provide quality of life assessment; and RA, the risk advisement module to notify risks at runtime.

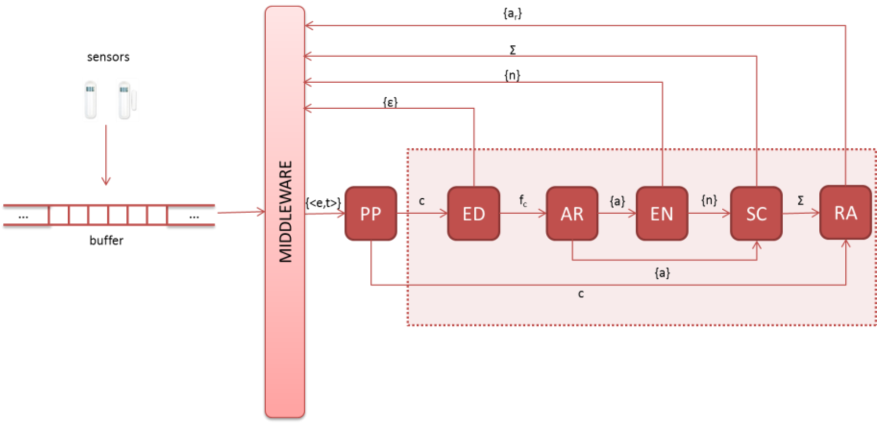

Figure 2 - The intelligent monitoring system.

The healthcare center receives notifications, summaries, statistics, and general information belonging to the users through a web application.

1.2 The Hierarchical Approach

eKauri is aimed at recognizing activities and habits of a user who lives alone. One of the requirements was to be cheap and non-intrusive. In other words, we use the minimum number of sensors depending on the user's home configuration, avoiding camera or wearable sensors. In particular, we decided not to use a camera for privacy reasons and in accordance with the requirements coming from the end-user of the proposed system. Moreover, the sensors were wireless and relied on wi-fi connection to send data to the collector. Let us note that we did not choose a wired solution because it was more expensive and intrusive. With these requirements we had to take into account the errors and noise coming from this configuration and we had to find a solution to avoid them. In fact, sensors are not 100% reliable: sometimes they lose events or detect the same event several times. When sensors remain with a low battery charge they are even less reliable. Moreover, also the Raspberry pi may lose some data or the connection with Internet and/or with the sensors. Also the Internet connection may stop working or loose data. Finally, without using a camera or wearable sensors we would not be not able to directly recognize whether the user is alone or if s/he has visitors. Although, as said, a wireless solution is not 100% reliable.

In order to solve this kind of limitations with the final goal of improving the overall performance of eKauri, we proposed an approach based on machine learning techniques. In this initial solution, we only considered motion and door sensors. The intelligent monitoring system continuously and concurrently listens for new data in a given window, according to a sliding window approach [6]. For each window, data are pre-processed and analyzed. As an example, let us consider the Figure 3 where once the current window recognizes a door event at time *tb*, it looks for the previous one in the window or before (in the example *ta*). Then, the period from that door events (i.e, *tb* - *ta*) is classified by the hierarchical classifier. Seemly, when the event *tc* has been recognized, the period from *tb* and *tc* is classified. Finally, the period from *tc* to the end of the window is classified. In case of no door events have been recognized, the period from *ta* to the end of the window is classified.

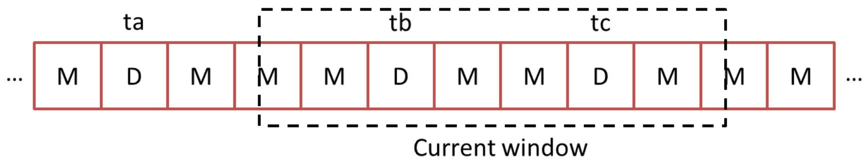

Figure 3 - An example of the sliding window approach.

The hierarchical approach, depicted in Figure 4, is composed of two levels. The upper is aimed at recognizing whether the user is at home or not, whereas the lower is aimed at recognizing whether the user is really alone or if s/he received visitors.

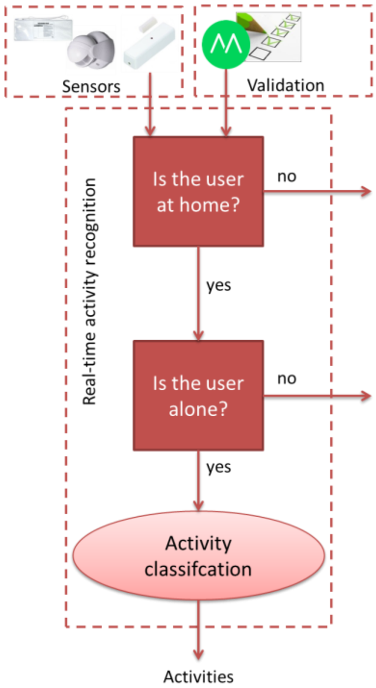

Figure 4 - The hierarchical approach.

1.2.1 Is the user at home?

The goal of the classifier at the upper level is to improve the performance of the door sensor. In fact, it may happen that the sensor registers a status change (from door closed to open) even if the door has not been opened. This implies that eKauri may register that the user is away and, in the meanwhile, activities are detected at user's home. On the contrary, eKauri may register that the user is at home and, in the meanwhile, activities are not detected at user's home. To solve, or at least reduce, this problem, we built a supervised classifier able to recognize if the door sensor is working well or erroneous events have been detected.

First, we revised the data gathered by the eKauri searching for anomalies, i.e.: (1) the user is away and at home some events are detected and (2) the user is at home and no events are detected. Then, we validated those data by relying on Moves, installed and running on the user smartphone. In fact, Moves, among other functionality, is able to localize the user. Hence, using Moves as an "oracle" we build a dataset in which each entry is labeled depending on the fact that the door sensor was right (label "1") or wrong (label "0").

1.2.2 Is the user alone?

The goal of the classifier at the lower level is to identify whether the user is alone or not. The input data of this classifier are those that has been filtered by the upper level, being recognized as positives.

To build this classifier, we rely on the novelty detection approach [7] used when data contain few positive cases (i.e., anomalies) compared with the negatives (i.e., regular cases); in case of skewed data. In particular, we rely on the approach presented in [8] that tries to estimate a function *f* that is positive on the dataset and negative on the complement. The functional form of *f* is given by a kernel expansion in terms of a potentially small subset of the training data; it is regularized by controlling the length of the weight vector in an associated feature space. The expansion coefficients are found by solving a quadratic programming problem, which we perform by carrying out sequential optimization over pairs of input patterns.

2. The Virtual Living Lab at a Glance

Developed by EURECAT, the Virtual Living Lab (VLL) is a software component designed to simulate sensor data in early phases of a project for testing purposes. This tool is capable of producing single or repetitive measures over time, depending on statistical models, configured via parameters. It simulates the measures like in a real scenario with a default ordinary behavior, with a probability of changing it to a certain degree, or produce data replicating preconfigured irregular behavior. This allows the VLL to simulate and test the standard operational mode of the project, and also be able to reproduce abnormalities that should be detected by the project implemented algorithms or sets of rules.

2.1 Functionalities

Two different operating modes are available, offline or online. The offline mode generates historical data to populate periods of time with information, whereas the online mode produces real-time data, simulating a real environment. This allows us to create historical data to be shown in interfaces, to receive/obtain prior (previous? / prior to which event?) data for algorithms, as well as to simulate the introduction of new data at every moment for the real-time consumption of the projects infrastructure.

The main objectives of VLL are:

- Giving support in architectures and protocols definition. Simulated sensor data can be produced at the very beginning of a study and, thus, they can be used to test components that rely on that at definition time.
- Detecting flaws on the architecture or protocol before building the real infrastructure.
- Perform stress tests. VLL can be configured for as many users as needed, therefore it will be used to stress tests in any moment of the development and considering different test environments and scenarios.
- Dissemination activity. Simulated data may be used to show functionality and purposes of a system through its interfaces without need of real data.

Apart of CONNECARE, VLL is adopted in further H2020 projects in which EURECAT is participating: MoveCare[6] and NESTORE[7]. In the former, VLL is used to generate environmental and health data (e.g., motion, doors, temperature, humidity, and weight). In the latter, it is used to generate environmental and health data as well as user profiling.

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[6] http://www.movecare-project.eu/

[7] https://nestore-coach.eu/home

It is worth noting that in the case of CONNECARE, generating health data was not useful because of the real data collected/obtained from the patients. Seemly, user profiling was not generated by using VLL but using data and habits from the recruited patients in the SMS.

2.2 Simulated Data

As described above, eKauri is composed of a network of environmental sensors that measures and monitors environmental variables: motion, temperature, gas leak, fire, CO escape, and presence of intruders, as well as outdoors activities through Moves. Given a map of a house, the VLL simulates motion sensors (i.e., if there are movements in the rooms) and opening/closing of doors and windows. In so doing, thanks to VLL we may infer in which room the user is and for how long, if s/he receives a visit and for how long, when s/he leaves the house and when s/he is back to home.

Figure 5 shows an example of VLL simulated environmental data for one user during two weeks. The horizontal axis represents the time (the 24h of a day) and each row represents a day. The colors represent in which room the user was at that time. This visualization helps to detect the usual habits of the users and spot anomalies. The normal habits of this users are: s/he usually wakes up between 7 and 8 am and during night s/he uses the bathroom two or three time. After waking up s/he spend some time in the living room and, then, uses the bathroom for a period a little bit longer than during night, possibly s/he has a shower. S/he usually spend all morning in the living room, some days s/he have a visit of someone, these periods can be visualized in the figure by those periods that have a door event and then multiple rooms are detected at the same time until another door event is detected. About 1 pm goes out and returns home about 3:30 pm, possibly s/he goes out to have lunch. Then, s/he stays in the living room until 5 pm, when s/he goes out again and returns about 8 pm. After arriving at home and spending some time in the living room s/he goes to the kitchen, and, then, spends about one hour in the dining room. Then, s/he stays in the living room until s/he goes to sleep between 9:30 pm and 12 am. However, there are some days with abnormalities in this pattern. For example, there are three days, Sept 25th, Sept 29th and Oct 2nd when the user stayed in bed until about 2:30 pm going to the bathroom every 2 hours. Those days, after waking up and a brief visit to the bathroom the user goes out until 8 pm, when returns home and follows hers/his normal habits. Other abnormal patterns are presented on Sept 28th, when s/he left home during night (about 4 am); Sept 30th, when s/he stayed for about 3 hours in the bathroom during the morning; and Oct 8th, when s/he did not return home during the afternoon until about 8 pm.

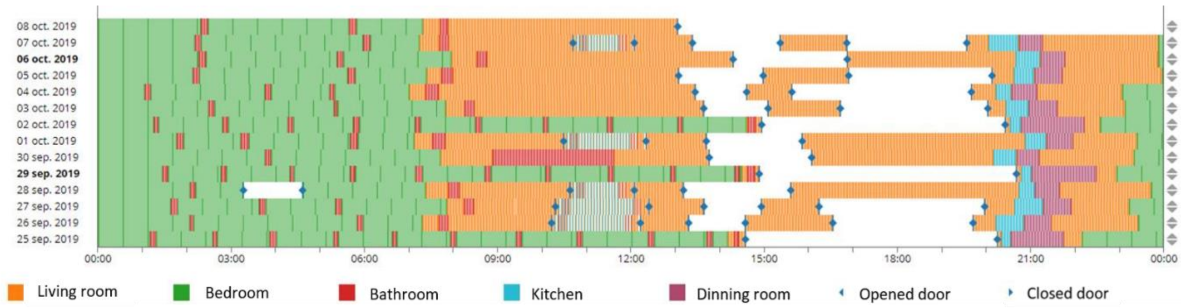

Figure 5: Example of VLL simulated environmental data for one user during two weeks.

3. Proof of Concept

In CONNECARE, VLL has been used to simulated environmental data, automated generated to study indoor habits and patterns of potential CONNECARE patients (e.g., elderly adults) to investigate the usefulness of introducing this kind of monitoring in conjunction with the SMS.

In the following we show some examples aimed at summarizing the experimental study that has been done to study how to fuse data from the VLL/eKauri with those from the SMS[8].

3.1 Improve Sleep Monitoring

The sleeping activity can be better monitored with the fusion of the data coming from the Fitbit wristband through the SMS and those from the domotics and environmental sensors (VLL/eKauri). In fact, the VLL/eKauri is capable of detecting the presence of a user in her/his bedroom but is not able to detect the activity (e.g. the difference between sleeping and reading a book). Data from the wristband help to detect the exact moment when the patient starts to sleep. On the other hand, the VLL/eKauri data could add information to the wristband by indicating in which room the user is at the moment that the wristband detects s/he is sleeping. In this sense, it would be interesting to detect when the user sleeps for example in the living room, (e.g., taking a nap or watching a movie).

Figure 6 shows an example of these cases. On the top, the figure shows the data gathered from the simulation with the VLL. On the bottom, it shows the sleeping data (whether the user is sleeping or awake) from the wristband. Relying only on the data coming from the VLL, we may infer that on Sept 16th and 17th the user had a similar pattern: waking up between 7 and 8 am and staying all morning in the living room until s/he leaves home about 2 pm. On Sept 18th, the data shows s/he stayed in the bedroom until about 2 pm when s/he also leaves home. On the other hand, analyzing the sleeping data from the wristband, we may see that on Sept 16th and Sept 18th the patient had a similar pattern sleeping until about 7 am and then having another sleeping period from 10:30 am to about 12 pm. On Sept 17th, the user woke up at 7:30 am and stayed awake all day. Thus, if we separately analyze the two types of data, a different inference is observed. Fusing the data, we may obtain a clearer picture about the patient's sleep pattern. On Sept 16th, the user woke up several times during night, during some of them s/he went to the bathroom, while sometimes s/he stayed in the bedroom. Then, s/he woke up at the usual hour (about 7 am) and stayed in the living room. During the morning, from 10:30 am to about 12 pm, s/he fell sleep in the living room. On Sept 17th, the user awoke two times to use the bathroom and then woke up at hers/his usual time. Finally, on Sept 18th, the user awoke four times during night to go to the bathroom

[8] In the examples, we refer to the VLL when talking about simulated, like in the figures, and to eKauri when we want to point out the benefits of adopting the sensor-based solution in real scenarios.

and then woke up at the usual time, but s/he stayed in the bedroom rather than going to the living room as usual. This could indicate s/he was not feeling well. Then, during the morning, from 10:30 am to about 12 pm, s/he fell sleep again.

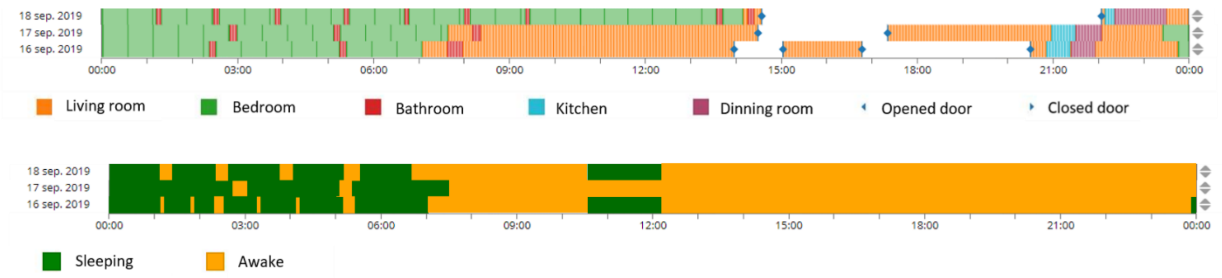

Figure 6: Example of the benefit of fusing environmental and sleeping data to better monitoring the sleeping activity.

3.2 Monitoring Bathroom Usage

Working with elderly people in previous projects, monitoring the bathroom usage by the elderly people, in particular during the night, is a relevant issue. In particular, in previous projects in which eKauri was adopted, the Intellilgent Monitoring sent alarms in case the user went to the bathroom during the night more than a given number of times (defined by the professionals).

Thanks to the VLL/eKauri and the SMS, we are able to study how using the bathroom during the night might affects the sleeping activity. In fact, using the data gathered by VLL/eKauri, we know if the patient went to the bathroom during the night. On the other hand, using the data coming from the wristband we know how much time it takes to the patient to fall sleep after waking up to go to the bathroom. Figure 7 shows an example in which the patient had different behavior when s/he uses the bathroom during night. On the top the data simulated by the VLL are shown, on the bottom the data from the wristband/SMS. Fusing together the two types of data, we can observe that on Oct 4th, the user went three times to the bathroom during night and s/he was capable of falling sleep almost immediately after that. On the contrary, on Oct 5th, s/he went two time to the bathroom during night, but it took almost one hour to fell sleep again.

Figure 7: Example showing how using the bathroom during night might affect the sleeping activity.

3.3 Improve Quality of Life Assessment

Adding the data gathered from eKauri to data on sleep from the wristband, it could be used to improve the QoL assessment, for example Anxiety and Depression (which has been explored in the T4.5 "Quality of Life Assessment System").

Figure 8 shows an example of a patient with an abnormal behaviour: s/he sleeps uncontinuously during the whole day. This behaviour could be a symptom of anxiety or depression. Let us analyse day by day, on Sept 20th the patient awoke several times during the night, even one of those times s/he stayed more than an hour awake in the bedroom, then s/he fell slept and managed to sleep until 7 am, but awoke several times to go to the bathroom. During the day, s/he stayed at home in the living room all day without eating and s/he took a nap of almost two hours in the living room from 2 pm to about 4 pm. The following day, the patient has a similar pattern. During night s/he awoke several times and on this day s/he stayed awake in the bedrom for about 4 hours. After sleeping about one hour, s/he woke up again and went to the living room where s/he stayed all the day. S/he fell sleep for about 6 hours in the living room. On Sept 22th, s/he slept just a few hours with a lot of awakenings, and about 3 am s/he went out. When s/he was back, s/he stayed awake in the living room until about 8 am when s/he fell sleep. Then, someone visits the patient and after the visit s/he left the house for about 5 hours. After returning home, s/he fell sleep in the living room for a couple of hours and then ate dinner, stayed in the living room for a while and went to sleep. In this case, although the sleeping activity data provide a lot of information about strange patterns in the patient's sleeping activity, the fact of having the information that the user left home in the middle of the night is crucial. In this case, the eKauri+SMS system should send an alerts to the professionals through the SACM reporting the anomalies registered during the night. Professionals will get in contact with the patient through the messaging function and, in case of need, they may decide to schedule a visit at patient's home or at the primary or social care facilities.

Figure 8 – Monitoring activity during the night to assess anxiety and/or depression.

3.4 Improve the Recommender System

As mentioned before, fusing together data from the domotics and environmental sensors with those from the SMS can also help to give smarter nudges and/or recommendations to the users.

As an example, let us consider a case in which the SMS suggests the patient to go outside and reach the steps goals, if it detects that the patient had not reached it in the afternoon. The corresponding message could be improved considering also the data from the sensors. In fact, eKauri can detect if s/he stayed all day at home in the bedroom. In this case, the message by the Recommender System should be improved asking the patient if s/he is feeling well.

Finally, the data from eKauri may be used to inform the SMS and, thus, the Recommender System in the case the patient forgot to wear the wristband. In fact, eKauri should detect that the patient goes outside but no steps are detected by the wristband. In this case, the Recommender System should send a message reminding to wear the wristband or asking the patient to check the synchronization of the device.

4. Conclusions and Future Directions

In CONNECARE, three levels of monitoring are proposed: basic, advanced, and assistive. Regarding basic and advanced monitoring, suitable services have been defined and developed according to the requirements gathered from the very beginning of the project and improved during the PDSA cycles. Basic monitoring tools are described in the deliverable D4.2 “Basic monitoring tools”, whereas the D4.3 “Advanced monitoring tools” illustrates the services developed for advanced monitoring together with the improvements made on the basic ones according to the CONNECARE iterative approach.

This deliverable summarizes the work done on assistive monitoring. At the kick-off meeting of all technical and clinical partners, it was decided not to use a sensor-based system (namely, the eKauri system by Eurecat) at patients’ home as was initially proposed. This was due to difficulaties in the definition and implementation of clinical studies of CONNECARE. Thus, a data simulator (namely, Virtual Living Lab, VLL) was adopted to simulate data from domotics and environmental sensors. Starting from the simulated data, we made a proof of concept to investigate if and how the data from a sensor-based system may improve the overall CONNECARE system with particular reference to the SMS. In particular, we showed that both the Quality of Life assessment system (described in the D4.5) and the Recommender System (described in the D4.6) may benefit from added sensor data.

As for the future directions, we envisage two approaches: 1) improving the VLL to simulate also data from other kind of sensors (e.g., bed, luminosity, temperature) and 2) experimenting the proof of concept in a controlled and closed environment using real data.

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