



D4.6 – Sensing technologies to monitor behaviours, emotions and physiological parameters – Final Version

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E-VITA – European-Japanese Virtual Coach for Smart Ageing

E-VITA (EU PROJECT NUMBER 101016453)

WP4 – Standards, Norms & Interoperability

D4.6 – Sensing technologies to monitor behaviours, emotions and physiological parameters (Final Version)

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Executive Summary

Deliverable D4.6 presents the main technologies constituting the e-VITA platform and deals with the sensor network and its optimisation in the user's environment. It consists of six main sections. After an introduction, Section 2 discusses the interoperability aspects relative to the use of several types of sensors and their integration into the e-VITA platform. Section 3 treats the sensor technologies identified for the e-VITA project, focusing on the technical sensors' characteristics in relation to use cases. Section 4 describes the mobile application that enables data exchanges between the Digital Enabler and the Data Fusion Platform. Section 5 presents a new methodology developed to optimize the configuration of the home sensor network using a simulation tool and Machine Learning. Finally, Section 6 summarizes the main results and concludes the document with perspectives and potential recommendations for the completion of the first prototype.

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Acronyms and Abbreviations

Acronym/Abbreviation	Explanation
ADLs	Activities of Daily Living
AIST	National Institute of Advanced Industrial Science and Technology
API	Application Programming Interface
CV	Cross validation
dB(A)	A-weighted decibel
DT	Decision Tree
ENG	Engineering
HR	Heart Rate
HRV	Heart Rate Variability
IAQ	Indoor Air Quality
IEQ	Indoor Environmental Quality
IMT	Institut Mines-Telecom
KG	Knowledge Graph
KNN	K-Nearest Neighbors
ML	Machine Learning
PIR	Passive InfraRed
PMV	Predicted Mean Vote
POC	Proof of Concept
SLE	Smart living environment
SpO2	Blood Oxygen Saturation
SVM	Support Vector Machine
UNIVPM	Università Politecnica delle Marche
USI	Universitaet Siegen

1. Introduction on sensing technology for e-VITA

From the two last decades one can see tremendous development of sensing technologies within the user's house and more generally, within the user's environment. Solutions have been designed and implemented more and more in a connected way, supporting the concept of Smart Home which is now well established in Europe, Japan and other countries. Generally, a Smart Home is equipped with different types of sensors which monitor environmental signals; they can be completed with sensors that monitors biomedical and vital signals and track activities of the user's daily life through actimetric signals, to provide the user with assisted, safe and comfortable living, for instance through fall detection and prevention embedded sensors.

We can distinguish three categories of sensors: those which are worn by the user and aim to sense physiological parameters (User Related Devices), those which measure physical quantities useful for assessing the level of comfort and the quality of the indoor environment (Environmental Devices) and those installed in the home to monitor user behaviour and activities (Home-Based Devices). For the e-VITA prototype, we combine these types of sensors to make inference of simple situations of the users in their environment, for instance postures, localisation in the home and the users' physiological states (see also deliverables D3.5 and D5.5). Contextual information is exploited by the interactive voice-based coaching system, knowledge graphs and Dialog Manager. There is a need of a good interoperability between the sensors, in particular at the fusion stage (see D5.1) and the targeted e-VITA applications, e.g. physical exercises, activities of daily living (ADLs), fall prevention. The e-VITA consortium, in particular partners contributing to WP4 have done a selection among existing sensing technologies in the market and among industrial e-VITA partners like the Delta Dore environmental sensors (motion sensors, door sensors, safety sensors), the NEU company (brain activity measuring device) but also taken from external technologies providers; for instance, the Netatmo devices for measuring environmental parameters like temperature or the EnOcean sensors for the experiments in Japan, and also different wearable sensors to measure physiological parameters like Oura Ring which is an alternative to the smartwatch.

To this aim, the document consists of six sections. The section 2 is devoted to the interoperability aspects relative to the use of several types of sensors; in this section we can find the approaches that are used for these different types. The section 3 covers the sensor technologies selected for the e-VITA prototype; this section is divided according to the types of sensors. The section 4 deals with the IMT mobile application allowing data exchanges between the digital enabler and the data fusion platform and eventually the section 5 presents the works that have been carried out to optimize the configuration of the home sensor network using the Smart Living Environment (SLE) simulation tool. The section 6 concludes the deliverable with perspectives and potential recommendations for the first prototype completion. A list of references and a set of appendices are provided at the end of the document.

2. Interoperability specifications for sensors integration

This section covers the chosen and implemented approaches that allow the devices interact with the e-VITA platform.

There are different ways in which a device can communicate with the platform; it primarily depends on the category to which the device belongs. The differences among the two categories are related on how the e-VITA platform accesses the device data, thus a specific solution is provided for each category. The two categories are the following:

- **PUSH:** the device itself sends the data to the platform directly or via a dedicated gateway.
- **PULL:** the measurements captured by the device are stored into an external cloud of the vendor and made accessible through secured proprietary REST API. In this case, the e-VITA platform needs to periodically read the data via API.

The communication methods are briefly described below, but it is important to underline that this aspect is widely documented in chapter 1 of D4.2 *Interoperability and standards guidelines for EU/Japan (Intermediate Version)* and also in chapter 1 of D6.12 *Reusability analysis – first releases*.

The e-VITA Manager provides different capabilities and interfaces to access the different devices:

- **Via REST APIs:** two interfaces are used by devices to send data: *send_data* and *send_file* APIs.
 - o *send_data* REST API: this functionality allows **PUSH** devices to send data to the platform and in particular smart home sensors or wearable devices can send measurements detected by their sensors to the platform and coaching devices (robots) can send text messages to the platform to forward them to RASA Dialogue System, in order to be analyzed and to produce a response toward the User.
 - o *send_file* REST API: this functionality allows **PUSH** devices to send files to the platform and in particular the supported file type is currently an audio file in WAVE format to be used as input for the emotion detection component in order to extract the specific emotions detected in the audio file. In the future it could be supported more file types (.e.g. video formats). Coaching devices (robots) are the only type of devices that are allowed to send audio files.
 - o REST APIs for third-party integrations: this functionality allows e-VITA platform to collect measurements from **PULL** devices: for this device type, measures are directly sent by the devices and stored in an external cloud of the vendor; e-VITA platform periodically reads the data from the cloud and imports the measurements into the platform. Therefore, in this case, the e-VITA platform must obtain the device data by accessing the cloud service related to them: the platform allows users to directly access with his credential to the specific cloud service before registering the relative device, in order to give the permission to e-VITA platform to get the measures from the cloud, using the REST APIs made available from the service.

Specific details about these features in the paragraph 2.1.3 of D7.4 *e-VITA Platform Architecture – Final Version*.

Inherent in interoperability, in addition to the aspect of sending measurements from devices to the platform, is also **retrieving stored measurements**. Within the e-VITA platform, the **FIWARE Orion Context Broker** [1] is used to manage context information collected from devices or sensors; this component is used to access data coming from devices, gateways, or robots, using the ETSI NGSI-LD API [2] interoperability standard.

The objective of the context broker is to store the transformed and harmonized raw data coming from the devices. Moreover, exploiting its features, this component is also used by other components of the architecture (the RASA Dialogue Manager, Data Fusion component, etc.) to suggest to the user, for instance, specific activities depending on the status of one or more sensors deployed in the environment.

- **Via WebSocket:** within e-VITA platform the WebSocket message handling is enabled, backed by a message broker, which has been appropriately configured. It is a bidirectional, full-duplex, persistent connection between a Client and a Server. Once a WebSocket connection is established, the connection is open until the client or server decides to close this connection. It is therefore made available to devices a mechanism that need two-way communication that does not rely on opening an HTTP connection. Basically, the type of integration developed through the e-VITA WebSocket is the same as the *send_data* REST API, what changes is the technology provided.

3. Sensing Technologies

The sensing technologies that make up the e-VITA platform are the basis of the multiple applications that the virtual coach offers the user. The sensing technologies offer significant opportunities to collect a huge volume of data useful to achieve the objectives of the e-VITA project. In the project, we selected not only publicly available devices, but also state-of-the-art solutions developed by the consortium's industrial partners, with a single concern: to best capture the user's condition.

The devices used in e-VITA (Table 1) are organised into three domains: User-Related Devices, Environmental Devices, and Home-Based Devices.

User-related devices	Huawei Band 7	
	Oura ring	
	NEU XB-01	
	uSkin pillow	
	Support device	<div style="display: flex; justify-content: space-around;"> <div style="text-align: center;"> <p>Smartphone</p>  </div> <div style="text-align: center;"> <p>Tablet</p>  </div> </div>

<p>Home-based devices</p>	<p>Delta Dore sensors</p> <p>DMB TYXAL+ sensor DMBD TYXAL+ sensor DO TYXAL+ sensor</p> 
	<p>EnOcean sensors</p> <p>ETC-PIR (Motion sensor) ETB-OCS (Door sensor)</p> 
<p>Environmental devices</p>	<p>Netatmo Smart Indoor Air Quality Monitor</p> 
	<p>EnOcean ET9-RHT (Temperature and Humidity sensor)</p> 

Table 1. Devices that compose the e-VITA platform.

3.1. User-Related Devices

User-related devices aim to detect the user's physiological parameters. Target applications of e-VITA include the user's emotional state, general health in terms of diet, physical activity and sleep quality.

The selected devices meet certain criteria. First, from a functional point of view, these devices provide consistent measurements and transmit them in a controlled manner (interoperability, security) to the

platform. Secondly, these devices are worn by the user to best capture his or her parameters but are non-invasive and can be used on demand according to the user's objectives.

3.1.1. Oura Ring

The OURA system with the OURA ring is aimed at people who want to live health-conscious lives and who are interested in further improving their well-being and who do not want to wear a fitness bracelet. The ring is particularly interesting for people who suffer from sleep disorders due to illness or other reasons and who are looking for ways to improve their sleep in an alternative way without taking medication.

Oura Ring 3rd generation is a ring-typed wearable device that fits on a finger and measures the user vital parameters such as body temperature, HR, and HRV, and determines the quality of sleep. In e-VITA project, Oura ring provides useful information regarding the health and activity status of the older adults to provide personalized advice from the virtual coach. The technical characteristics, measured parameters, and functionalities of the OURA app can be found in deliverable D4.5.



Figure 1. Oura ring 3rd gen

Unlike most fitness trackers, which are almost always worn on the wrist, the OURA ring collects data on one finger. According to the manufacturer, the most accurate data is provided by the index or middle finger. While its predecessors were primarily intended to track sleep, 3rd version of the ring also provides more information and analysis on the course of the day. With an update planned for the near future, the ring will also provide more information on sports activities.

From the collected data, the OURA app recognises correlations, learns the wearer's behaviour patterns, and detects when something is wrong. As the app records and analyses data over longer periods of time, unhealthy behaviour patterns of the wearer are detected and highlighted. The app regularly provides advice on how to cope with the day and how to improve sleep quality. In addition, the concrete tips aim to change the user's behaviour in the long term. In this way, the user can improve his or her well-being by changing behaviour.

The recommendations and suggestions of the OURA app can make the user more aware of the need to be more mindful of his or her body. If values worsen, several factors can be experienced, such as the time one goes to bed or gets up, bedroom temperature, diet, time spent in front of the screen, etc.

With the OURA Ring 3rd generation, the manufacturer introduced an app membership in the form of a subscription. The subscription model is not mandatory to use the ring, but otherwise, after six months of free membership, you only have access to the charge level, daily sleep, activity and recovery.

Therefore, it is recommended to subscribe for 5.99 euros per month. This way, you get the full functionality.

Regarding the protection and security of the OURA ring data, the company states that the collection, processing and storage of all data is GDPR-compliant, i.e. all data are encrypted, anonymised and aggregated.

3.1.2. Huawei Band 7

The smartwatch is a device that can bring added value to the e-VITA application as it allows recording vital parameters (HR, HRV, SpO₂, pulse oximetry, sleep, activity) and recording signals such as actimetry (fall detection, movement) in a non-invasive way for the user. It also offers the possibility of having a historical record of the acquired data via the application on the smartphone connected to the wearable device.

The search on the market for a device that could capture all this data, that was GDPR compliant, affordable, global available, that had certain technical aspects of connection and had APIs available, led to the selection of several solutions. UNIVPM, USI, ENG, AIST and IMT had started negotiations with the Life+ company, as reported in the previous D4.5, for the use of their devices. However, as Life+ devices could not provide direct access to signals from embedded sensors, it was necessary to develop specific APIs to gain access to this data on the cloud. After several discussions with the head of Life+, for industrial and economic reasons, it became impossible to develop these APIs, so we abandoned this idea. UNIVPM then got in touch with Garmin Health for the use of Garmin smartwatches in e-VITA. The discussion continued with the CEO of Fitrockr, a company that provides access to data from Garmin devices by providing a platform for accessing raw data (via REST API). The high cost of the service (400 euros per month for 20 users), however prompted this solution to be put aside. The idea of using Medisana devices (cheap wrist-bands) was also discarded given their unavailability in France and on the Japanese market. The Xiaomi MI Band 7 was then selected. However, the Chinese company Xiaomi, when asked to create an account for e-VITA integration testing by ENG, did not reply, forcing another solution to be chosen. Finally, after further brainstorming, the choice came to the Huawei Band 7, an affordable wearable device available on the global market and GDPR compliant. ENG then carried out an initial integration test phase (creating a developer account) and data acquisition using available rest APIs.

Huawei band 7 is a wrist-band wearable device that can monitor blood oxygen saturation (SpO₂), heart rate (HR), steps, sleep status, stress status, and so on. The device incorporates accelerometer sensor, gyroscope sensor and optical HR sensor (Table 2).



Figure 2. Huawei Band 7.

Display	1.47-inch AMOLED 194 x 368 pixels
Sensors	Accelerometer sensor Gyroscope sensor Optical heart rate sensor
Network	802.11 b/g/n (b/g/n = Wi-Fi 4) Bluetooth 5.0 LE
Dimensions	44.35 x 26 x 9.99 mm
System requirements	Android 6.0 or later iOS 9.0 or later
Connectivity	2.4 GHz, BT5.0, BLE
Operating System	Huawei HarmonyOS
Weight	29 g
Price	50 euros
Battery life	14 days for typical use
Other features	5 ATM water-resistant

Table 2. Huawei Band 7 specs.

The main point of contact is the Huawei Health app (Figure 3), where all the data collected by the wristband's sensors are displayed and analysed.



Figure 3. All collected data are managed through the Huawei Health app and the values are displayed as graphs.

Health parameters are displayed both on the watch itself and on the Health app. In addition to the current values, the tracker also shows previous workouts. Huawei's "Running Ability Index" function has also been introduced in the Band 7. Using a scale, the wearer's performance value during a run is displayed and compared with that of other users. In addition, the tracker shows the training regime of the past seven days, recovery status or estimated recovery time until the next intensive training session, and VO2Max. The tracker has a wide range of fitness functions. Data synchronisation with Google Fit is not possible. However, Huawei is currently working on a way to synchronise data with Strava, which should be implemented later this year.

The tracker provides a graphic overview of steps taken, movement time and activity time. In a submenu, the wristband also provides the calories burned during the day and the distance travelled. The app goes into even more detail, dividing the steps into different categories such as running, walking and climbing.

The "Healthy Living" set of parameters, which aims to ensure a healthy routine, goes beyond simply tracking physical activity. In addition to steps taken and activity time, stress levels and sleep and wake times are considered. Categories are displayed in different colours along with their respective values, and the app can also remind the user of unmet goals if desired. The wristband can also provide a notification if the user has not moved in a while, for example if he or she is sitting at a desk.

The Health app also offers the possibility to create training and running plans, in which personal preferences and performance are set. The app can then remind you of upcoming training sessions. The app also prepares weekly and monthly reports, in which all data is marked and partly displayed. The data is also compared with previous training periods.

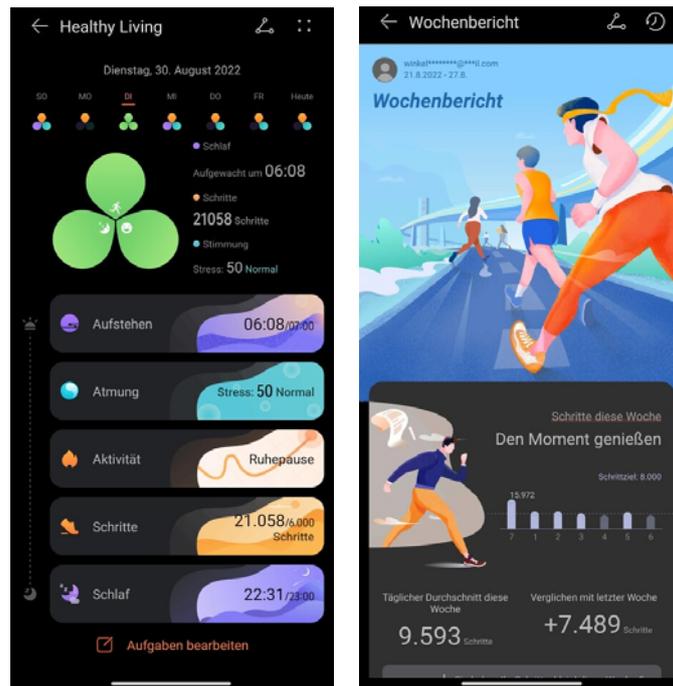


Figure 4. Healthy Living summarises several health-related parameters and also provides weekly and monthly reports.

The sleep detection of the Huawei Band 7 recognises light, deep and REM sleep phases. The watch itself merely displays the sleep duration upon waking; for details, one needs to consult the Health app. Here, the various sleep phases are displayed graphically, and times and percentages are also provided. The entire sleep period and individual phases are analysed, and the software provides suggestions on how to improve sleep quality. The wristband can wake the user with its vibration function, but only at set times and not according to sleep phases.



Figure 5. Huawei app provides data on individual sleep phases and evaluates sleep quality.

The Huawei Band 7 supports the tracking of 96 different types of exercise, six of which collect more data or evaluate them more intensively, such as jogging or walking. The tracker shows the pulse as a value and through a colour scale during exercise. In addition, you can monitor distance, duration, calories burned, maximum time, average speed, cadence and step length during walking. After establishing distances, e.g. after each kilometre or mile during a walk, the watch provides a summary of the last kilometre/mile and estimates the intensity of the workout. The tracker is also able to recognise continuous movement, if desired, and the display asks if it should start recording the workout. The software then asks if the training should be stopped if no movement is detected for several minutes.

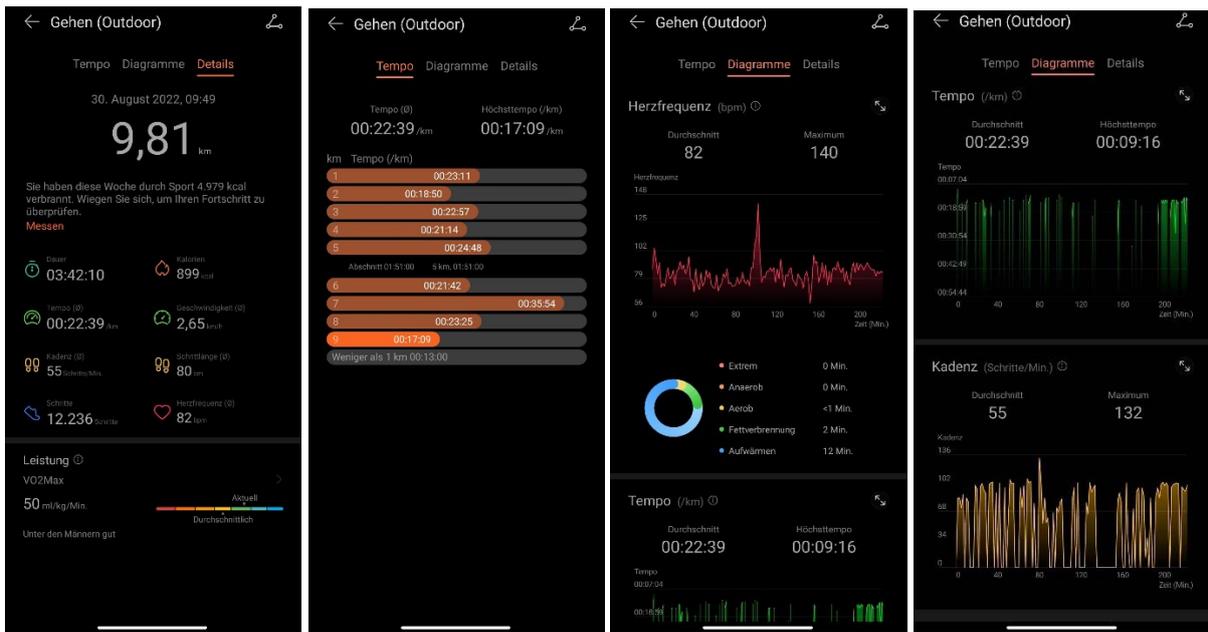


Figure 6. Exercise data displayed in the Health app.

3.1.3. Brain Activity Monitor: NEU XB-01

There are several wearable devices on the market for monitoring brain activity. These include bands that record the electrical activity of the brain using specific sensors (EEG, PPG) placed along the forehead to detect brain activity. The wearable devices then communicate with an application to interpret the data into valuable information for the user. Just as a smartwatch can provide information on HR, such a device can provide information on the user's brain activity and cognitive state.

Table 3 shows the most popular wearable brain activity monitors on the market.

DEVICE	PRIMARY APPLICATION	COMPONENTS	POWER SOURCE	CONNECTIVITY	COMPATIBILITY	PRICE
INSIGHT 2 Company: <i>EMOTIV</i>	Medical, Gaming	EEG sensor	Rechargeable battery	Bluetooth	Android, iOS, Windows, OSX, Linux	470€
MINDWAVE Company: <i>NEUROSKY INC.</i>	Lifestyle	EEG sensor	Disposable battery	Wi-Fi	Windows, OSX	360€
EPOC + Company: <i>EMOTIV</i>	Lifestyle, Gaming, Entertainment	Gyroscope, EEG sensor	Rechargeable battery, external source	Wi-Fi, Bluetooth, USB	Android, iOS, Windows, OSX, Linux	800€
MUSE Company: <i>INTERAXON</i>	Lifestyle, Medical	EEG sensor, Accelerometer	Rechargeable battery	Bluetooth, USB	Android, iOS, Windows, OSX, Linux	300€
BRAINLINK LITE Company: <i>MACROTELLECT</i>	Lifestyle	EEG sensor	Rechargeable battery	Bluetooth	Android, iOS	200€
XB-01 Company:	Lifestyle	PPG sensor, Accelerometer	Rechargeable battery	Bluetooth, USB	Android, iOS	100€

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Table 3. Wearable devices to monitor brain activity

- The Emotiv Insight 2 is a wearable EEG headset that can transmit meaningful brainwave data wirelessly to a smartphone or computer in high spatial resolution. The device offers 5 EEG sensors and 2 reference sensors providing information on brain activity. The measurements are based on six key cognitive and emotional metrics: focus, stress, excitement, relaxation, interest, and engagement. These measurements allow an individual to monitor their cognitive health and well-being.

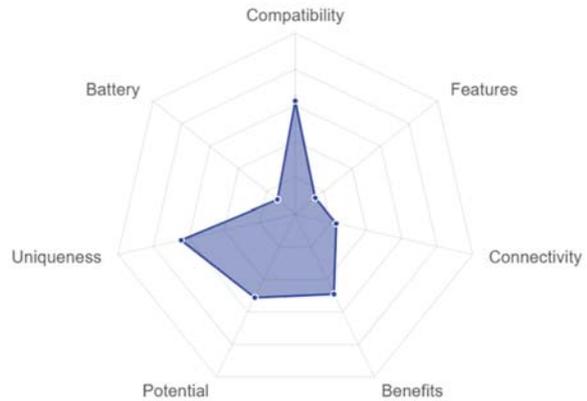


Figure 7. Emotiv Insight 2

- The NeuroSky MindWave is a wearable headset that measures brainwave signals and monitor attention levels. The brainwave signals and the attention duration can be observed on the computer, and the information are used for example to determine how well a student is learning. This device also comes with ten different software programs that range from fun entertainment to advanced education.

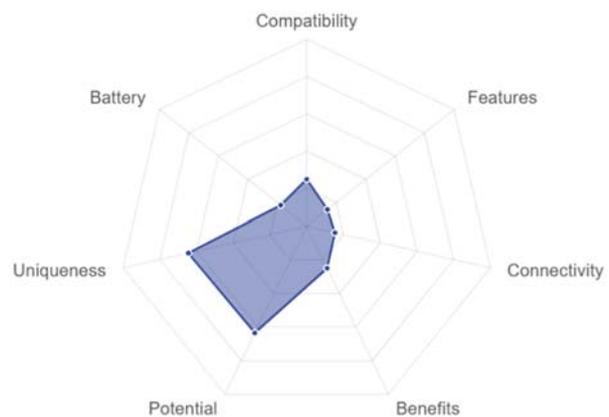


Figure 8. NeuroSky MindWave

- The Emotiv Epoc+ is a neuro-signal acquisition interface for human and computer interaction. It uses sensors to detect electric signals produced by the brain to detect player thoughts, feelings and expressions. It can be connected wirelessly to most PCs. The neuroheadset can be used for controlling an electric wheelchair, a keyboard and playing hands-free games. The

wearable device comes with two options, one is with the EPOC package and the other is the EEG package. The EEG options has all the benefits of EPOC plus access to raw EEG data.

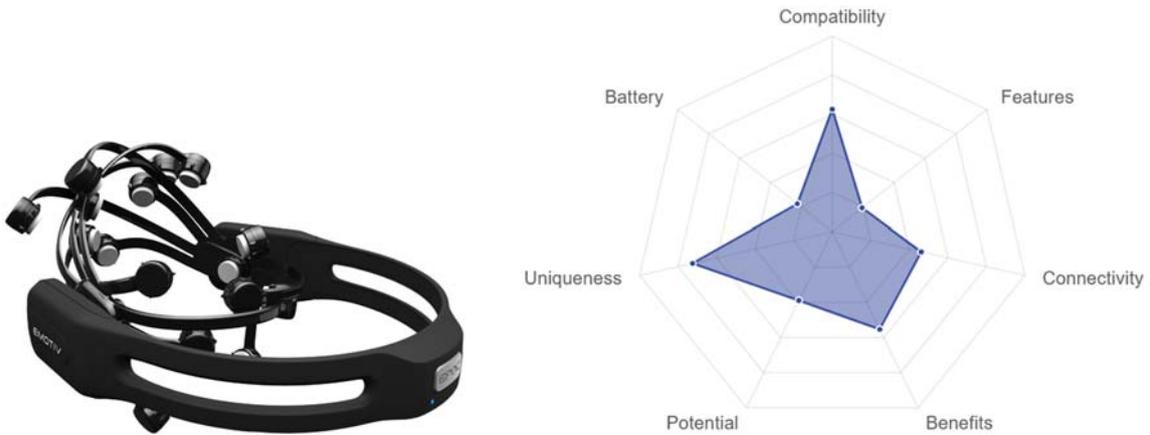


Figure 9. Emotiv EPOC+

- The InteraXon Muse is a mental activity tracking device that helps reduce stress and settle the mind. The wearable device uses 7 sensors that are applied to the occipital lobes. Once in place, they record brain activity which is then translated into actionable data and sent to a tablet, smartphone, or computer. Muse helps apprehending and managing emotions to improve cognitive well-being, more specifically concentration and calm.



Figure 10. InteraXon Muse

- The BrainLink Lite EEG headset helps achieve mental fitness, focus on goals and improve work efficiency by learning to control the brain, achieve better results in relaxation and meditation with over 100 applications.



Figure 11. BrainLink Lite

- The NEU XB-01 is a small brain activity measuring device that can monitor the activity of the brain, the blood flow and pulse rate. The XB-01 can be used in scenarios such as cognitive function training, movement and cognitive function training, stress coping, learning.



Figure 12. NEU XB-01

After comparing the aforementioned devices, we decided to use the NEU XB-01 in e-VITA due to the availability of proprietary apps and services to support cognitive training, the device's low cost and its ease of use and non-invasiveness. Brain training is one of the most important aspects when it comes to maintaining and improving cognitive functions. However, there are individual differences in the human brain and not all brain training programs may be effective on an individual basis. NEU's Active Brain Club (ABC) app measures the brain with the ultra-compact brain activity sensor (XB-01) that allows the visualization of brain activity in real-time. This allows users to activate their brain consciously, allowing for a much more effective customized personal brain training program compared to conventional methods.

The ABC is a service that uses NEU XB-01 to provide cognitive function training while measuring brain activity and is intended for senior citizens who want to maintain their brain functions and improve their performance. The ABC consists of two courses: a "basic" and "standard" course. The "Basic Course" combines the XB-01 and a visualization application for brain activity. For example, by presenting cerebral activity casually, an individual's focus and memory ability can improve, leading to an improvement in work productivity and efficiency in learning. Since continuing training is vital, the "Standard Course" includes several added programs such as neurofeedback-type cognitive function training, aerobic exercise and cognitive function training, stress coping, and so forth.

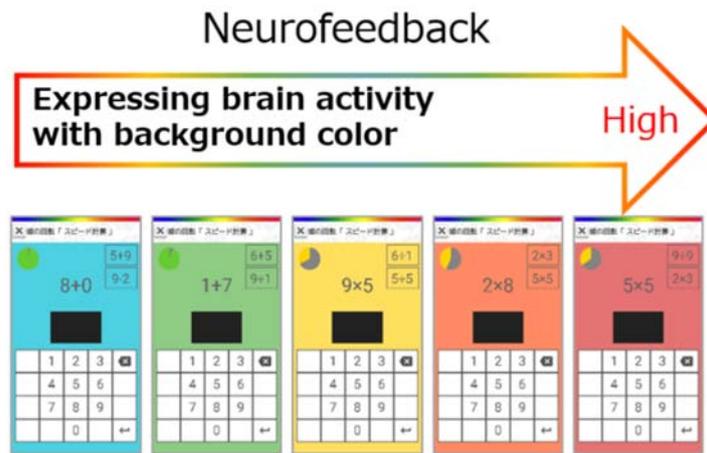


Figure 13. The brain activity is displayed in the background through changes in the colour of the screen, in real-time

The ABC also includes an application called the “Brain Meter”, which allows users to visualize brain activity during various tasks and exercises. This “Brain Meter” is also a useful tool to find contents such as tasks and exercises that are best suited for each individual.

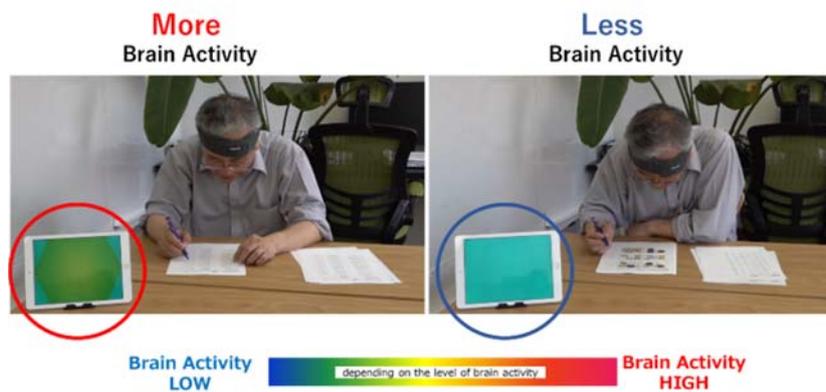
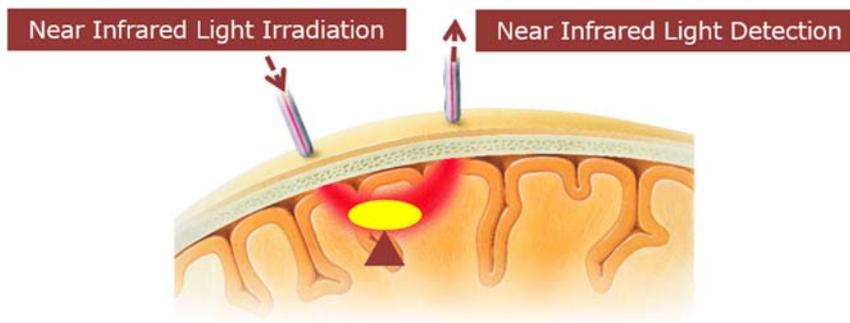


Figure 14. Brain Meter

XB-01 is an ultra-compact integrated sensor-type device that weighs only 30 grams (battery included) and measures 80 x 40 x 13 mm. The built-in lithium-ion battery allows approximately 4 hours of continuous measurement and can be charged via a USB power supply. Its “butterfly-style” design bends in the middle, allowing the XB-01 to conform easily to any individual’s forehead. Brain activity is measured using NIRS technology and the brain’s rate of blood flow change is measured using weak near-infrared light. The light source is a LED with a measurement point of 1 channel. The sensors are placed at 3cm intervals on the head to visualize changes in brain activity. NIRS uses near-infrared light in the wavelength range of 800nm, which can pass through human tissues but is absorbed by haemoglobin, making it a very convenient wavelength for measuring humans. Since brain nerves require oxygen and glucose when they are active, haemoglobin increases in areas where brain activity is high, and the transmission of near-infrared light decreases. Optical topography technology can visualize brain activity by measuring the amount of change in this light. It is a safe technology because it does not use radiation or chemicals to make measurements. Data are transferred via BLE 4.0 in real-time to any smartphone or tablet, making it possible to measure brain activity with a data acquisition frequency of 10Hz.



Blood volume increases as oxygen is sent to the brain and concentration change of hemoglobin is measured with light.

Figure 15. The principle behind the NEU XB-01 sensor is its ability to measure the brain's blood flow with light

3.1.4. uSkin Pillow

With increase in age, we see a rise in poorer sleep quality, increase in lonely death and an increase in pressure injuries by prolonged contact over a particular body part. Moreover, sleep has proven to be an important indicator of several physiological and mental health issues. Disrupted sleep has been associated with cognitive problems, dementia, Alzheimer's and Parkinson's. Furthermore, it is also a common symptom of mental illness such as depression and anxiety.

While several research have taken place in developing tools to better understand sleep, they have been rather intrusive to the subjects. Our goal is to develop an unobtrusive method to monitor sleep.

Implementation: By using the distributed 3-axis force measurements, various data about the user can be obtained, such as breathing (due to the slight, rhythmic head movements that the head performs during breathing in and out), change of sleeping posture, restless sleep, and so on. As the sensors are placed in different parts of the pillow, this allows us to gather data from different sections of the pillow and varying head placements. Each tri-axial sensor measures three-axis force: a magnet is placed elastically above a three-axis magnetometer. As forces are applied to the sensor, the magnet displaces, and thereby the three axis forces can be measured. As for the dimensions of the sensors, each sensor is 6mm wide, 5mm long and 5.5mm high.

We implemented two layouts for the sensor placement. In V1, the uSkin Pillow included 16 tri-axial sensors, distributed inside the pillow, see Figure 16. In the new V2, the uSkin Pillow includes only 13 tri-axial sensors, yet covers a larger area of the pillow, see Figure 17.

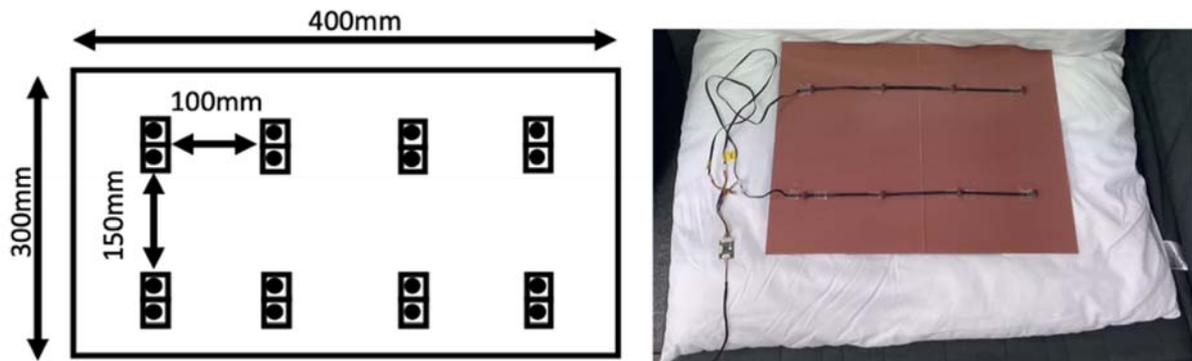


Figure 16. uSkin Pillow V1.

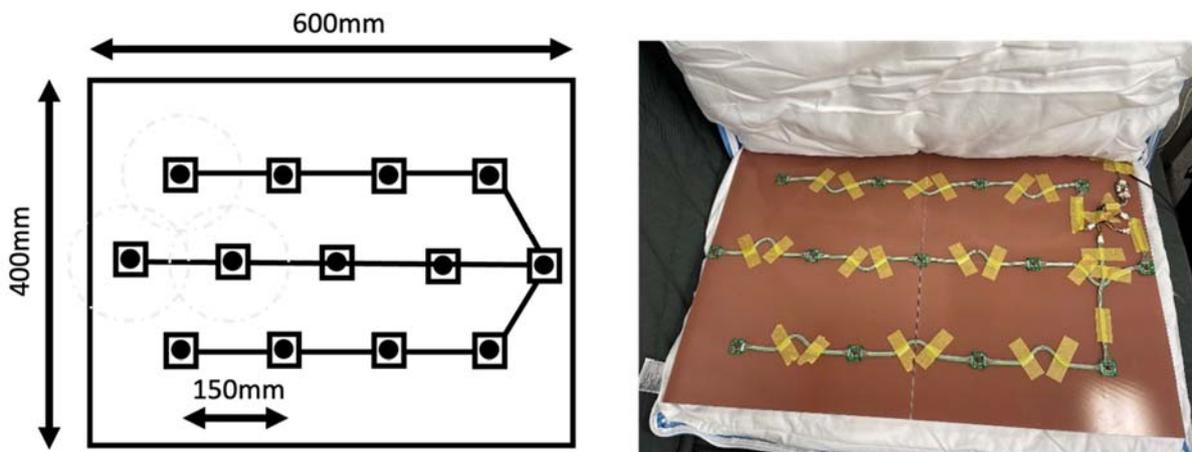


Figure 17. uSkin Pillow V2.

We implemented software that detects the following signals: movement count, sleep time, awake time, average respiratory rate, sleep apneic episodes, sleep orientation (side, back, front/belly), please see Figure 18.

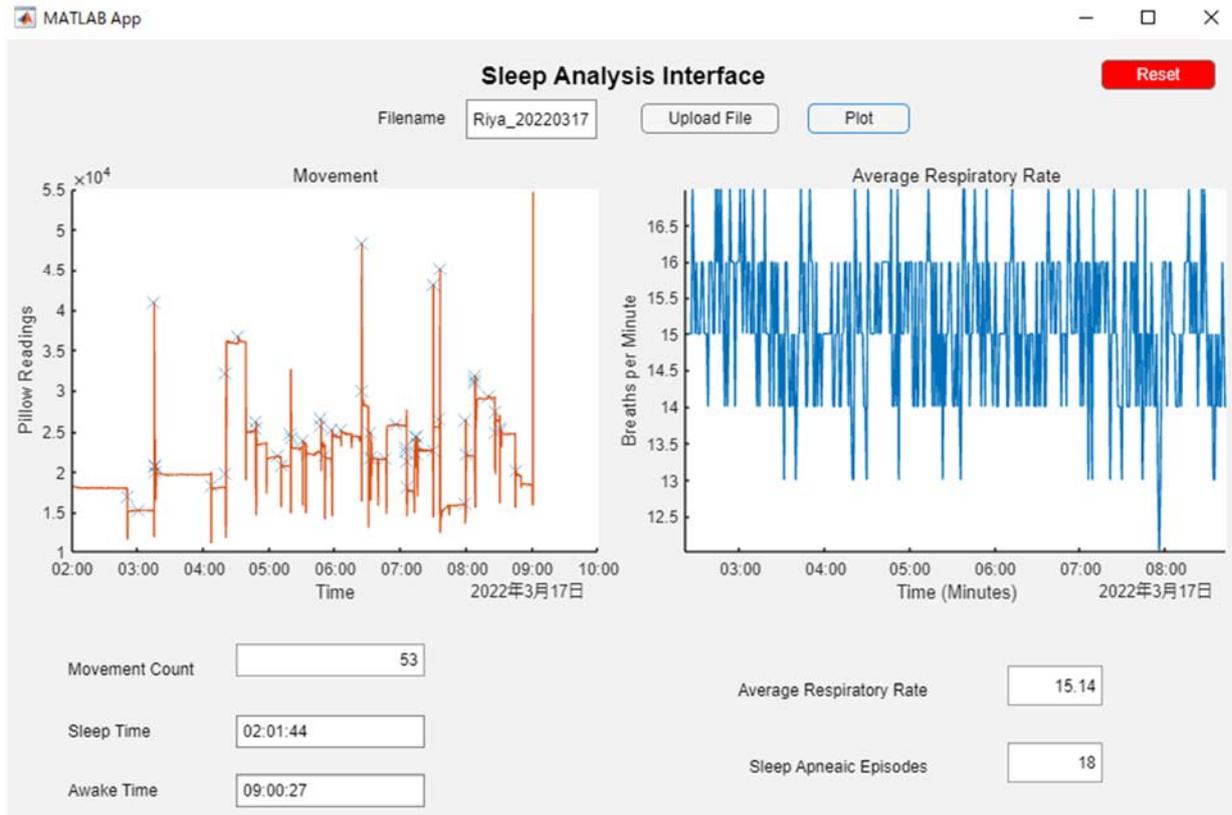


Figure 18. uSkin Pillow Sleep Analysis Interface.

3.1.5. Support device

For the management and configuration of the e-VITA virtual coach, end users are provided with a support device consisting of a smartphone or tablet, chosen based on user preference.

The device is used to send and receive messages to friends/family and to update users on social events in which they can participate. Training reports, physiological data collected during the day, methods of performing physical exercises, etc. are also displayed on that device. The different user support apps (ABC, exercise chatbot, nutrition chatbot, etc.) also require a smartphone or tablet to be used.

In choosing the devices, the Android operating system was preferred due to the low-to-medium cost of the devices, the flexibility of the system as open-source and the presence of applications related to the sensors chosen to be part of the e-VITA platform. Based on the minimum technical requirements (Table 4), several smartphones and tablets were identified on the market (Table 5) as suitable devices for the e-VITA platform.

NETWORK	<i>Technology</i>	GSM / HSPA / LTE
PLATFORM	<i>Operating System</i>	Android 10

MEMORY	<i>Internal RAM</i>	64GB 4GB
CONNECTIVITY	<i>WLAN Bluetooth GPS</i>	Wi-Fi 802.11 a/b/g/n/ac, dual-band, Wi-Fi Direct 5.0 Yes
FEATURES	<i>Sensors</i>	Accelerometer, Gyroscope, Compass, Proximity

Table 4. Minimum technical requirements of Android devices

Smartphone	Tablet
Samsung Galaxy A12 Samsung Galaxy A31, A32 Samsung Galaxy A41, A42 Samsung Galaxy A50, A51 Xiaomi Redmi Note 8 Xiaomi Redmi Note 9 Xiaomi Poco M3 Xiaomi Poco X3	Samsung Galaxy Tab A7 Samsung Galaxy Tab S5e Samsung Galaxy Tab S6 lite Lenovo Tab M10 Lenovo Tab P10

Table 5. Identified Android support devices

3.2. Environmental Devices

Measurement of the well-being of ageing people in their living environment has become relevant, particularly in this period of pandemic. Since ageing people are increasingly encouraged to stay home to avoid risky situations, the measurement of their well-being in their homes plays an important role for the healthcare system that can continue taking care of them remotely. Moreover, an important aspect that needs to be considered is that older people prefer to live in their own homes instead of moving to nursing or care facilities.

3.2.1. Well-being of Ageing People based on Indoor Conditions

Well-being is affected by socio-economic aspects, environmental settings and conditions, social exclusion, health and mental status. It is therefore a concept that embraces several aspects and has a great impact on older people's life. Considering that older people are more susceptible to the indoor environment because of their weak immune system and the large amount of time they spend indoors, the measurement of the indoor environmental quality (IEQ) is determinant for their health and well-being. The IEQ acceptance of older adults can be assessed by the following aspects: acoustic, thermal, visual comfort and indoor air quality (IAQ). All these aspects could be measured in the living environment to improve the well-being of older people and provide adequate services to them. For example, feedback, suggestions, or advice could be provided to the older users to optimize the indoor environmental conditions, e.g., opening a window when the IAQ is poor and/or drinking water if the air temperature is high in summer.

Therefore, among the objectives of the e-VITA virtual coaching system is to be used in personalized user-system interaction to promote patient engagement and compliance, supporting older users in improving their well-being and quality of life. The experience between the older users and the virtual coach could increase the involvement of the users in achieving goals, promoting a healthier lifestyle, and improving long-term behavioral change. In this context, the e-VITA coach will provide feedback and advice to older people to improve the IEQ in their living environment and subsequently their well-being and comfort perception using human-coach conversation techniques.

In this context, UNIVPM and AIST did a preliminary study to develop a scientific methodology to provide feedback and advice to older users based on IEQ monitoring [4]. Considering that IEQ is based on acoustic, visual, thermal and air quality comfort, the methodology consists of identifying the sensor network for monitoring IEQ in indoor environments and then implementing the heterogeneous database and developing a KG based on the measurement parameters to define the human-coach conversation between the virtual coach and the user.

Acoustic comfort in the living environment is an increasingly important topic for improving productivity and reducing anxiety for regular users in indoor environments. Literature reports that excessive noise levels into living environments cause annoyance, sleep disturbance, irritability and also long-term health effects, such as cardiovascular disease, heartillness, hypertension and psychiatric problems [5]. Older people are more vulnerable to noise because they are more sensitive to disturbance. Consequently, providing acoustic comfort is necessary to minimize the environmental noise and support the satisfaction of the inhabitants [6]. For the World Health Organization, all undesired sounds are noise [7] and acoustic comfort in living environments is ensured by the absence of unwanted sounds, by desired sounds with the right level and quality, and by acoustic activities that do not bother other people [8]. The indoor environments could be influenced by external, e.g. transportations, machine operations, neighborhood, etc., and internal noise, e.g. conversation, home equipment, indoor activities, etc. [7].

In [9] has been reported that in living spaces like nursing homes, poor acoustic quality might have an adverse impact on the behavior and well-being of older people and their informal caregivers, decreasing their everyday quality of life. Older and younger population showed differences based on acoustic preferences. Older people prefer lower background noise, relative to younger individuals, for practical and satisfactory communication. In fact, ageing people become less sensitive to high frequencies and low voice volume. However, hearing loss was shown to affect motor capability in older adults and increase the risk of falls, indicating that the acoustic environment in living spaces is far more critical than it often seems. For this reason, it is demonstrated that acoustic interventions in indoor environments could improve the acoustic comfort for older users, e.g. acoustic curtains, wall and ceiling absorbing panels, etc.

In the living environment, the acoustic comfort limit is 55 dB(A) and the acoustic safe limit is between 55 dB(A) and 65 dB(A). It is important to consider these thresholds to guarantee the well-being of occupants [10]. In this context, limits such as noise recommend less than 30 A-weighted decibels (dB(A)) in bedrooms during the night for good quality sleep could be considered, in particular, considering that older people suffer mostly of sleep disorders. In addition to this, the recommended night-time noise is less than 40 dB(A) of the annual average outside the bedrooms to prevent the negative health effects caused by night-time noise. When the noise level is higher than the acoustic safe limit (55 – 65 dB(A)),

the occupants could be exposed to risks such as decrease in comfort and cognitive performance for noise levels higher than 55 dB(A), stress responses (e.g., increase of electrodermal activity and cortisol) for noise levels higher than 65 dB(A) and physiological responses (e.g. heart rate variability and respiration rate) for noise levels higher than 70 dB(A).

Visual comfort for older people in living environments takes an important role, in particular, regarding the well-being and security of the user. In fact, the proper quantity as well as the quality of illumination is of importance when designing living environments for ageing people. Quantity refers to the performance of a task (a person needs sufficient light to complete a task), while quality refers to the distribution of brightness in the space (effects such as glare, veiled reflections and visual comfort are lighting quality problems). In this context, visual comfort is defined in the European standard EN12665 [11] as the subjective condition of visual well-being induced by the visual environment. Improved visual comfort, i.e., light conditions, contributes to the improvement of quality of life, prevention of falls and improvement in ambulatory ability, especially among older persons with low vision. In this context, optimal contrast by the use of colours in the living environment where the older person spends a substantial amount of time can prevent falls [12]. In particular, some pathologies in older people, e.g. cataract and glaucoma, cause the need to use more light, better quality, but especially to increase the levels of contrast. Based on that, measurement of luminance contrast levels and visual needs considerations provide the weaknesses of an existing environment and then the possibility to proceed with its optimization [13]. In the kitchen area, over the countertop minimum 500 lux is required. In the living room is suggested to have between 300 – 1000 lux throughout the space. In particular, areas close to the floor should be carefully illuminated with 100 – 500 lux to prevent falls and accidents. For lavatory areas, approximately 200 – 500 lux is required to prevent accidents [14].

Thermal comfort plays a pivotal role in the well-being of the population. It is defined as the state of mind which expresses satisfaction with the thermal environment and it is assessed using the Predicted Mean Vote (PMV) model that consists of four indoor climate parameters (ambient air temperature, relative humidity, mean radiant temperature and air speed) and two personal factors (clothing insulation and metabolic rate) [15,16]. Thermal comfort occurs at $-0.5 \leq PMV \leq 0.5$, while for sensitive and frail people, the suggested range is $-0.2 \leq PMV \leq 0.2$ [17]. For aging people, the health risk of exposure to rapid or extreme changes in environmental temperature presents challenges for thermal homeostasis. Thermal discomfort caused by indoor and outdoor environmental conditions (i.e. heat and cold) is a potential health risk, in particular, for older people with multiple co-morbid conditions [17]. This provides the need to tailor indoor environmental conditions to meet the thermal needs of occupants, a crucial consideration for health and well-being. For aging people with cognitive disease or stroke, providing an environment that satisfies the need of the user has a paramount role, since those users are coupled with a decrease in temperature discrimination. However, in the literature, several studies found no statistically significant age-related differences in the dependence of thermal sensation on operative temperature [18,19]. Contrary to that, recent studies revealed that older people have low thermal sensitivity and lower thermal sensation than the PMV model used in many standards, concluding that current thermal comfort models are potentially unsuitable for predicting comfort in an older population and may significantly overprescribe comfortable temperatures. Those studies have revealed that the optimum temperature for older people to achieve thermal comfort is higher than young adults with equivalent clothing insulation, owing to lower metabolic heat production. Furthermore, females tend to be more sensitive to cold temperatures and hence prefer warmer

temperatures. In [17], measures of air temperature and clothing are reported in order to mitigate potential thermal discomfort for sedentary older occupants living in residential cares. For the indoor air temperature, the values between 22.8 °C and 23.6 °C are considered a comfortable range over a year. A clothing range of 0.6 ± 0.1 has been derived from the non-dementia group. In [20], it is reported that residents of a nursing home in the Mediterranean prefer higher temperatures than caregivers and therapists. In general, field studies in buildings occupied by older people during the summer revealed that older people prefer higher temperatures than non-older adults. This preference for the higher indoor temperatures caused a higher energy consumption for heating in nursing homes in the winter period. However, the same study confirmed that, in winter, older people use clothing adjustment to adapt to the environment. In this case, the acceptability of indoor air temperature for 90% of residents ranged from 21.6 °C to 22.9 °C.

Urban air pollution affects the health of citizens. Several diseases are associated with air pollutions, e.g. cardiovascular morbidity, chronic obstructive pulmonary disease, pneumonia, etc. Since older people spend most of their time indoor, decreasing physical activity, they are subjected to a reduction of immunological defenses and chronic diseases which make them more at risk from the effects of air pollutants. In addition, during this pandemic period there is an increase in severe acute respiratory syndromes due to the transmission of coronavirus 2 (SARS-CoV-2, the virus that caused COVID-19). To reduce the transmission of the virus by ensuring social distancing and at the same time monitoring the physical activity carried out by the older people, in [21] the authors implemented a real-time localization system (RTLS) integrated with inertial measurement unit (IMU) sensors. Carbon monoxide (CO), carbon dioxide (CO₂), formaldehyde, total volatile organic compounds (TVOC), particulate matter up to 10 micrometers size (PM₁₀) and particle matter up to 2.5 micrometers in size (PM_{2.5}) are the measures for the indoor air quality evaluation. In [22], it has been demonstrated a relation between high PM_{2.5} concentrations and respiratory diseases, blood pressure and autonomic function influence in older people both in winter and summer. Furthermore, the same study demonstrated a correlation between exposure to PM₁₀, TVOC, CO₂, bacteria and fungi and the progression of respiratory chronic disease in the same cohort. Also in [23], it has been demonstrated the relation between the exposure to PM₁₀ and the increase in the occurrence of acute respiratory symptoms and reduced lung functions in aging people. Another age-related problem caused by poor IAQ is poorer cognitive performance [24]. Since the measurement of CO₂ can provide a good estimation of the quality of IAQ (when the CO₂ level is lower than 1000 ppm in an indoor environment), coaching methods could be realized in order to apply ventilation strategies and behavioral changes [25].

Feedback and recommendations to improve the well-being and comfort of older users living in their homes are provided using the measurement parameters acquired through the sensor network installed in the users' homes. For the specific use case of IEQ monitoring, the heterogeneous set of sensors that could be installed in the living environment could be characterised as in Figure 19 and described in Table 6. Specifically, the measurement parameters are air temperature, relative humidity, CO₂ concentration, sound level and light level. Feedback and advice to users in the e-VITA project are provided through robots, e.g. Nao, DarumaTO and CelesTE, but also through Avatars and Androids.



Figure 19. Sensor network for IEQ monitoring in the living environment.

Sensor	Measured parameter	Measuring range	Accuracy
Air Temperature sensor	Air temperature	0 °C to 50 °C	± 0,3 °C
Humidity sensor	Relative humidity	0 to 100 %	± 3 %
CO2 sensor	CO2 concentration	0 to 5000 ppm	± 50 ppm (0 to 1000 ppm) or ± 5% (1000 to 5000 ppm)
Acoustic level	Noise level	35 to 120 dB	± 0,1 dB
Comfort sensor	PMV	-3 to +3	± 0,1
Lux meter	Light level	0 to 99999 lux	± 3 %

Table 6. Sensors installed in the living environment to measure the IEQ.

Knowledge Graphs (KG) are developed to provide feedback and advice to the user through the virtual coach. KG are networks of entities and connecting links (edges). The entities represent real-world objects, events, situations, or concepts, and the edges denote relationships between them. Relationships can be directed or undirected, and they can also have properties. KG are visualized in a graph structure and can be stored in a graph database. We focused the attention on labelled property graphs, where properties include specific information about entities.

Compared with traditional relational databases, graph databases are flexible and easily extendable, and they focus on the relationships rather than on the data elements. This is a considerable advantage in present-day data problems which deal with heterogeneous data and many-to-many relationships.

For this specific use case, KG are used for storing knowledge for the coaching system and enabling the dialogue manager to talk about the relevant interesting topic. The dialogue manager recognizes the

main concepts in the user's utterance, maps them onto the entities and relations that it knows about, and having recognized the user's intent, it makes knowledge base queries to find the necessary information to answer the user query.

Figure 20 shows an example of KG in the environmental sensor domain, and the effect of environmental state on well-being. For easy readability, the nodes are color-coded in the figure. The blue nodes represent some of the different factors that can be measured to estimate the indoor environmental state, e.g., in this figure: room-temperature and CO₂ concentration. The yellow nodes denote what kind of recommended actions are available given the sensor values of a particular state. Green and red nodes represent the state of comfortableness and uncomfortableness, which can increase depending on the optimal or inadequate values of the environmental factors. The main concept of indoor environmental state is colored lilac and well-being deep green.

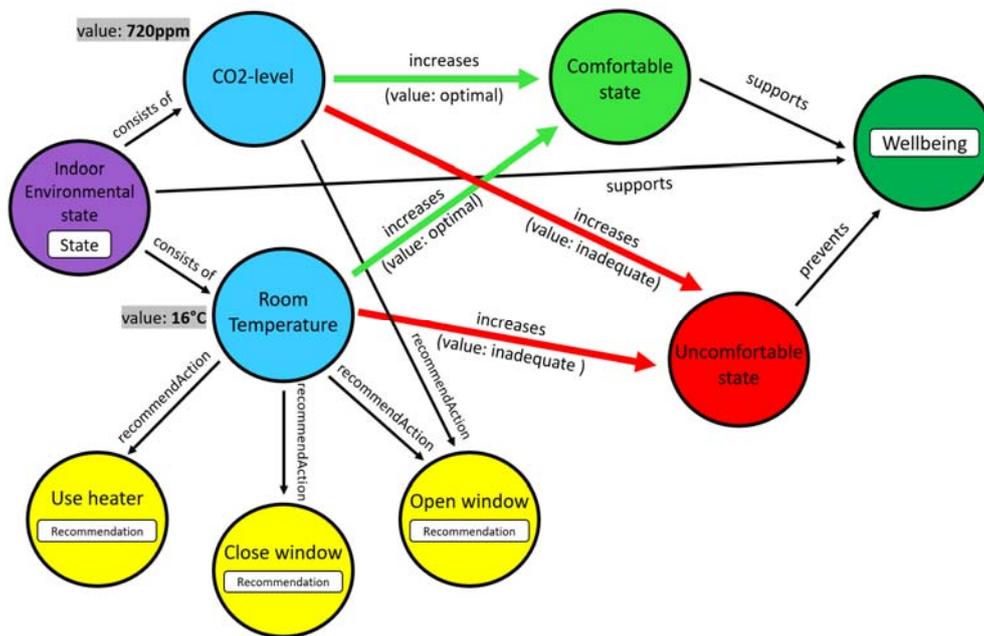


Figure 20. Example of Knowledge Graph based on room temperature and CO₂-level for IEQ monitoring.

More nodes can be easily added to the graph with appropriate links. For instance, Figure 21 shows a graph that also includes noise level and humidity as environmental factors, while another topic, namely sleep disorder, is added to the graph by linking it to the node uncomfortable state as an example whose probability is increased by the uncomfortable state. It is thus possible to trace back the reasons for sleep disorder by following first the link *increases likelihood* to the *uncomfortable state* and then following the *increases* links from this state with the value *inadequate*, to the nodes which represent environmental factors. Consequently, we can infer that the probability of sleep disorder is increased by uncomfortable state, which is increased by the inadequate valued environmental factors like CO₂ concentration, humidity, noise level and room temperature.

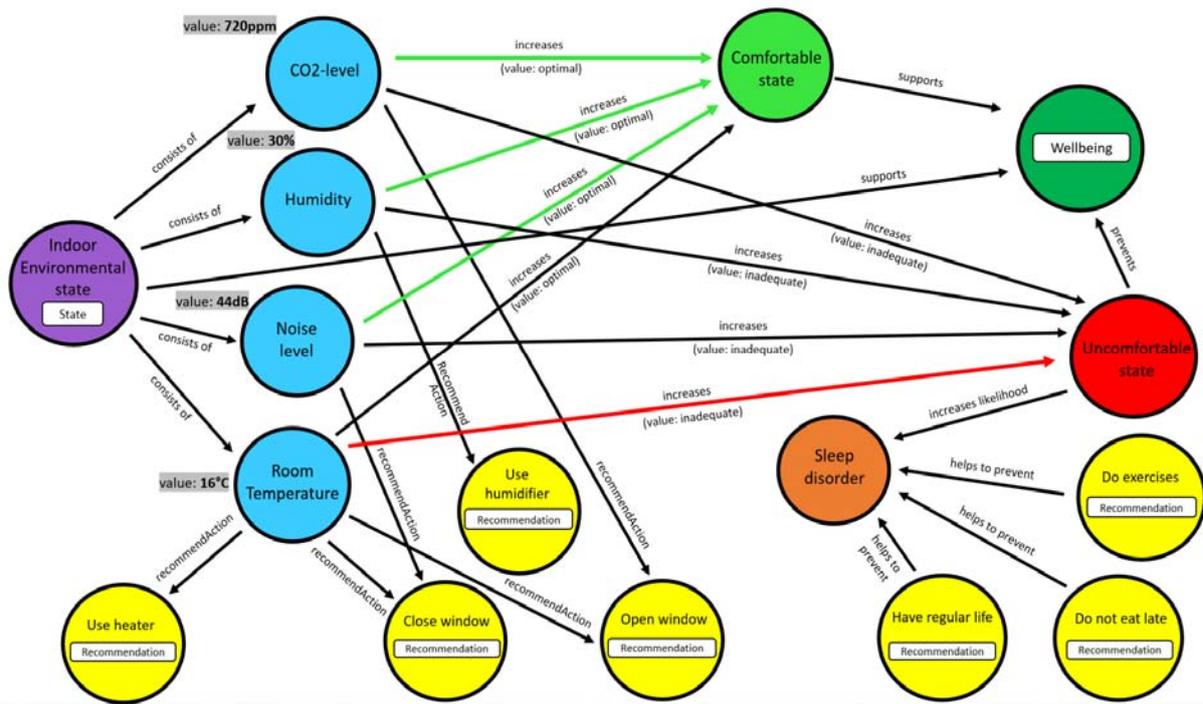


Figure 21. Knowledge Graph based on IEQ monitoring.

The graph also shows how the different environmental sensors support the user's feeling of comfortable or uncomfortable state, depending on if the value measured by the sensor is “optimal” or “inadequate”. Table 7 shows the threshold values for “optimal” and “inadequate” labels for each of the measured quantities. This is a simplification of how the sensor information is represented in the graph, but since the continuous-valued sensor information cannot be represented in the graph, we assume that there is a component that estimates the sensor state into the labeled categories, and subsequently the dialogue system will use the category label for estimating the value of the environmental state in its further processing.

Measured parameter	Labels	
	Optimal	Inadequate
Room temperature	20 °C – 25 °C	< 20 °C > 25 °C
Humidity	30 % – 50 %	< 30 % > 50 %
CO2 concentration	< 1000 ppm	≥ 1000 ppm
Noise level	≤ 40 dB	> 40 dB

Table 7. Threshold values for “optimal” and “inadequate” labels for the measured parameters.

The sensor values in Figure 21 are given as examples of a particular state where e.g., room temperature is 16 °C and CO₂ concentration is 720 ppm. In this hypothetical situation, CO₂ measurement point to

the comfortable state since 720 ppm guarantees a good IAQ, while room-temperature that the system finds too low points to the uncomfortable state, and thus it can suggest the user to close the window and use the heater.

The KG supports small interactions like:

Q: “What kind of environmental factors does the environmental state consist of?”

A: “There are four different factors: room temperature, noise level, humidity, and CO₂ concentration.”

Q: “I see. How can the CO₂ concentration support my well-being?”

A: “If the value is optimal, less than 1000 ppm, then the air quality is good, and it increases the comfortable state which supports well-being.”

Q: “Can you tell me what I can do to prevent sleep disorders?”

A: “The following helps to prevent sleep disorders: regular lifestyle, do not eat late, and do exercises.”

Q: “What causes sleep disorder?”

A: “Uncomfortable state can increase the probability of sleep disorder. Do you want to know what uncomfortable state increases?”

Q: “Yes, tell me what increases the uncomfortable state.”

A: “Uncomfortable state is increased by inadequate levels of CO₂, humidity, noise and inadequate air temperature.”

Q: “Thank you.”

A: “Thank you. Is there anything else you would like to know?”

Q: “No thanks, that is all.”

A: “Anyway, I notice that the room temperature has dropped to 16 °C. Please close the window and turn on the heater.”

Q: “Oh, thanks very much for the recommendation. I'll do this.”

A: “Thank you.”

In conclusion, we saw a scientific methodology to provide a data-driven human-coach conversation for ageing people in the living environment can be developed. The conversational strategy is based on IEQ measurements acquired at the user’s home since it is identified that the measure of acoustic, thermal, visual comfort and indoor air quality have an impact on the well-being and comfort of ageing people. The KG is used to identify the relationships between the measurements and the well-being of the user and to develop human-coach conversations based on these relationships.

3.2.2. Netatmo Smart Indoor Air Quality Monitor

It is well known that the comfort and health of older residents depends on the indoor environment. In this sense, an IAQ monitoring device can help by providing advice on what to adjust to ensure comfort and well-being at home. Measuring key data at home therefore allows to live in a healthy environment.

Following the above-described methodology to provide feedback and advice to older users based on IEQ monitoring, the Netatmo Smart Indoor Air Quality Monitor has been identified in D4.5 as the device to measure environmental parameters.

The Netatmo Smart Indoor Air Quality Monitor tracks temperature, humidity, IAQ, and noise level in the home. The hardware and technical characteristics of the device are reported in D4.5.



Figure 22. Netatmo Smart Indoor Air Quality Monitor

All measured parameter values are displayed in the app on the smartphone or tablet. The app also indicates whether the values pose a health hazard to the user and provides suggestions on how to fix the problem.

The device is implemented in the e-VITA platform so that measured parameters are retrieved via its API, through which the Digital Enabler can be queried to retrieve historical measured data.

Specific details about how the e-VITA platform retrieves the device measurements in paragraph 2.1.3 of D7.4 – *e-VITA Platform Architecture – Final Version*.

3.2.3. EnOcean Sensors

In 3.2.2, the Netatmo Smart Indoor Air Quality Monitor was introduced as a suitable device for measuring environmental parameters. However, Netatmo is not available in Japan, so the following EnOcean sensors are used in the experiments conducted in Japan.

3.2.3.1. Temperature and humidity sensor – ETB-RHT



Figure 23. EnOcean ETB-RHT

This sensor monitors the temperature and humidity in the home.

The hardware and technical characteristics of the device are listed in Table 8.

Device	EnOcean ET9-RHT
Manufacturing Company	iTEC
Link	https://www.itec-corp.co.jp/index.php?ETx-RHT
Mechanics & Design	Polycarbonate weather-resistant grade material Designed for indoor and outdoor use
Size	82mm(W) x 24mm(D) x 12mm(H)
Weight	Approx. 22g
Sensors and measurements	<p>Temperature (T)</p> <ul style="list-style-type: none"> - range: -20°C to 60°C (resolution 0.08°C) - accuracy: ±0.7°C (-20°C to 5°C) / ±0.4°C (5°C to 60°C) <p>Records frequency: every 6 minutes</p> <p>Humidity (H)</p> <ul style="list-style-type: none"> - range: 0% to 100% of relative humidity (resolution 0.39%) - accuracy: ±3% (20% to 80% @25°C) / ±6% (Other humidity @25°C)
Connectivity	<p>Protocol: EnOcean (EEP: A5-04-03)</p> <p>Modulation method: FSK</p> <p>Frequency: 928.35MHz</p> <p>Data rate: 125kbps</p> <p>Transmitting power: 1mW (EIRP)</p> <p>Certification standard: ARIB STD T-108</p>

Power	Solar cell																																																																																	
Operating conditions in the dark	24h operation in the dark: 2 hours in 400lx environment 72h operation in the dark: 7 hours in 400lx environment																																																																																	
Operating environment	Temp: -20°C to +60°C Humi: 0% to 90% (No condensation)																																																																																	
Message content	Digital signal (Measured temperature and humidity and unique sensor ID)																																																																																	
Data format	Protocol: EnOcean (EEP: A5-04-03) <table border="1" data-bbox="523 734 1385 1025"> <thead> <tr> <th>Offset</th> <th>Size</th> <th>Bitrange</th> <th>Data</th> <th>ShortCut</th> <th>Description</th> <th>Valid Range</th> <th>Scale</th> <th>Unit</th> </tr> </thead> <tbody> <tr> <td>0</td> <td>8</td> <td>DB3.7...DB3.0</td> <td>Not Used (= 0)</td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td>8</td> <td>8</td> <td>DB2.7...DB2.0</td> <td>Humidity</td> <td>HUM</td> <td>Rel. Humidity (linear)</td> <td>0...250</td> <td>0...100</td> <td>%</td> </tr> <tr> <td>16</td> <td>8</td> <td>DB1.7...DB1.0</td> <td>Temperature</td> <td>TMP</td> <td>Temperature (linear)</td> <td>0...250</td> <td>-20...+60</td> <td>°C</td> </tr> <tr> <td>24</td> <td>4</td> <td>DB0.7...DB0.4</td> <td>Not Used (= 0)</td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td>28</td> <td>1</td> <td>DB0.3</td> <td>LRN Bit</td> <td>LRNB</td> <td>LRN Bit</td> <td></td> <td></td> <td>Enum: 0: Teach-in telegram 1: Data telegram</td> </tr> <tr> <td>29</td> <td>1</td> <td>DB0.2</td> <td>Not Used (= 0)</td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td>30</td> <td>1</td> <td>DB0.1</td> <td>T-Sensor</td> <td>TSN</td> <td>Availability of the Temperature Sensor</td> <td></td> <td></td> <td>Enum: 0: not available 1: available</td> </tr> <tr> <td>31</td> <td>1</td> <td>DB0.0</td> <td>Not Used (= 0)</td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> </tbody> </table>	Offset	Size	Bitrange	Data	ShortCut	Description	Valid Range	Scale	Unit	0	8	DB3.7...DB3.0	Not Used (= 0)						8	8	DB2.7...DB2.0	Humidity	HUM	Rel. Humidity (linear)	0...250	0...100	%	16	8	DB1.7...DB1.0	Temperature	TMP	Temperature (linear)	0...250	-20...+60	°C	24	4	DB0.7...DB0.4	Not Used (= 0)						28	1	DB0.3	LRN Bit	LRNB	LRN Bit			Enum: 0: Teach-in telegram 1: Data telegram	29	1	DB0.2	Not Used (= 0)						30	1	DB0.1	T-Sensor	TSN	Availability of the Temperature Sensor			Enum: 0: not available 1: available	31	1	DB0.0	Not Used (= 0)					
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Table 8. EnOcean ET9-RHT specifications

The system for transmitting the data measured by this sensor to the e-VITA platform is described in Section 3.3.2.3.

3.3. Home-Based Devices

The solutions known as smart home are generally divided into three parts in terms of use: the HVAC control part, which is the structural and historical field of electronics within homes and buildings; the control part for opening systems, automatic controls and lighting, to which can now be added the control of household appliances; and finally, the security part, which corresponds to systems whose function is to protect property and people within the home or its immediate environment.

To this vertical division, we can add, in a transversal manner, the dialogue and visualisation solutions which have been strengthened in recent years thanks in particular to the generalisation of connectivity solutions on the Internet network. These solutions have enabled users to visualise and control the equipment in their homes using their smartphones. It should also be noted that the maturity of voice solutions proposed by major players in advanced technologies has facilitated the link between the occupants and the systems in the home.

The current issues concerning the use of energy, its optimisation in terms of consumption and production with the arrival of self-production solutions have pushed the building industry to increase the need for sensors to measure the various energy flows. The arrival of the electric vehicle is also a new element that tends to make previously (very) compartmentalised systems more and more

interconnected. This is true for the equipment inside the house but also for connecting the house with the outside, i.e. with the neighbourhood, the district, the energy suppliers or the providers in general.

The general trend in home systems is therefore towards the interconnection of the systems themselves but also of the uses, while preserving their autonomy for basic uses.

In the home, there are generally sensors that measure physical quantities useful for assessing the level of comfort and the quality of the environment.

In HVAC solutions, we therefore find indoor and sometimes outdoor temperature sensors, and more and more often humidity sensors. All these sensors make it possible to adapt and control the cooling or heating generators, whatever the technology used, to maintain the occupant's environment in a comfortable zone. Window sensors can be added to minimise energy loss to maintain a comfort level in an energy consuming environment when the window is open. Similarly, the addition of presence or motion detectors can optimise energy consumption according to the presence or absence of occupants.

The advent of high energy performance buildings has been accompanied by the need for better knowledge of indoor air quality and therefore sensors for CO₂, VOCs, etc. The level of air quality allows occupants to have an indicator of the need to ventilate rooms. Some work has also aimed to infer the presence of occupants from the CO₂ sensors emitted by the occupants. This orientation has the advantage of minimising the number of sensors while increasing the knowledge of the environment.

In some regions, radon sensors are also common, when the geology of the territory encourages their installation or when legislation makes them mandatory.

Security solutions also use several sensors which can be divided into two main groups: anti-intrusion sensors (mainly motion sensors, opening sensors and cameras) which help to ensure the security of the home against intrusion, and technical sensors (smoke detectors, water leakage detectors, gas detectors, etc.) that provide an alert in case of fire, water leakage and flooding risks.

Some of the equipment used to ensure the safety of property and people in the home, apart from the sensor network, is dedicated to communicating warning information: these include indoor and outdoor sirens and transmitters that relay the warning to users or monitoring organisations.

It should be noted that there are detection solutions based on automatic systems and, conversely, automatic system control solutions linked to security. For example, Delta Dore offers an intrusion detection solution when an attempt to open the shutters is detected. Conversely, the detection of smoking can lead to the automatic opening of the shutters and the triggering of lighting to facilitate the exit of the occupants.

Many measuring devices have been introduced in the dwellings: measurement of electricity, water or gas consumption to allow the occupants to access tangible information on their consumption. This orientation has been driven by regulations for new housing (for instance: RT2012 in France) but also by a general context of awareness of practices and their impact on the environment.

There are many flow sensors (electrical, water, gas, etc.) which also provide a good understanding of the practices, activities and habits of users and occupants.

The energy transition in which home equipment control systems are involved is based on a twofold movement: better knowledge of usage to personalise control and better feedback to the user in order to guide him towards virtuous behaviour. The transversality of data from the home requires a hardware architecture (gateway, native IP, etc.) that can centralise it and a logical structure (language, ontology, metalanguage, profile, etc.) that can extract knowledge from it.

There are gateway-type solutions that make it possible to link with cloud uses, services, learning, big data. On the other hand, end-to-end IP solutions are increasingly common (6, LowaPan, Thread, ...) sometimes accompanied by the logical structure (Matter).

3.3.1. Delta Dore Sensors

Delta Dore manufactures and sells a wide range of home automation and security products, including alarm systems. For the e-VITA project, several types of sensors marketed by Delta Dore are of interest to meet the requirements of the project: the motion detector and the window/door opening detector. A detail description has been done in the deliverable D4.5 section 4.3.1.

This chapter deals with the characteristics of the motion sensor and the improvement to meet the e-VITA requirements.

The specific components and features of a Delta Dore alarm system may vary depending on the model and configuration, but the most common elements include the sensors for detecting movement, door and window openings, smoke and other hazards. The alarm system also includes a control panel that is the central hub of the system, receiving signals from the sensors and managing the response to any alarms. The communication between the devices and the control panel of the alarm system of Delta Dore is wireless.

The third element that composes the alarm system are the devices that allow the so-called “alarm response” which includes alarm triggering. It is a loud siren that is designed to alert the occupants of the building and deter the intruder. If the system has a gateway or is connected to a gateway, it can alert the user by sending a notification on his/her smartphone or, if the system is monitored by a monitoring service company by sending an alarm to it.

The alarm system of Delta Dore is battery powered which means that each device is powered by battery. Even the control panel is powered by battery. The life cycle of the system is 10 years. To reach that life cycle it is needed to optimise the power consumption of the sensors.

How do sensors work?

Sensors are designed to detect changes in their environment and transmit a signal to the control panel when a certain threshold is reached.

A motion sensor uses infrared technology to detect changes in the temperatures of its surroundings. When the sensor detects a sudden increase in temperature (such as that might be caused by a person moving through its field of view), it sends a signal to the control panel.

The power consumption of the sensor depends on the frequency it analyses the environment and the frequency it transmits a signal because they are the two power consuming functions of the sensor.

To reduce the power consumption of the IR motion sensor, it is possible to increase the scanning frequency of the IR function. The limit is depending on the speed of the target that must be detected; in the case of alarm use case, it can't be less than the time a person passes through the of the sensor field of view, otherwise it is possible for an intruder to enter a house without triggering the alarm system.

It is also possible to decrease the frequency or the number of signals that are transmitted to the control panel by the sensor.

There is a technical standard for alarm systems that requires that certain signals to be sent regularly to the control panel to ensure that the sensor is working properly. It is understood that although these signals consume a lot of energy, they cannot be suppressed.

However, the pattern of signals that are sent when there is a detection can be optimised in the use case of intruder detection.

One of the means that has been introduced is the inhibition time, which allows the transmission to be stopped for a certain period of time before sending the end-of-detection signal. As shown in Figure 24, the inhibition allows to reduce considerably the number of transmitted signals. For the use case of intrusion detection, this works because the aim is to detect the intruder as long as he/she is in the house. This is the way Delta Dore motion detectors work for their alarm systems.

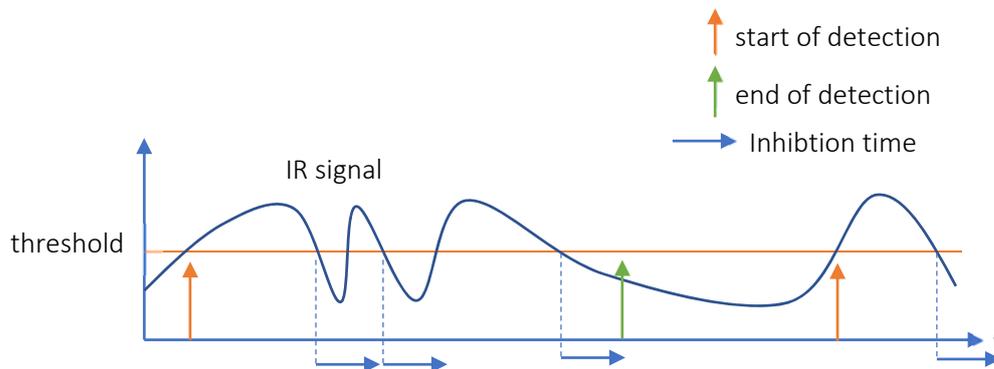


Figure 24 : IR motion detector diagram

The characteristics of Delta Dore's motion sensor meet most of the requirements of the e-VITA project to monitor the movements and activities of the inhabitants. The range and the field of view are established to detect people in a room; the accuracy is good enough to accurately detect movements and distinguish it from other sources of motion or noise; in alarm system application it's particularly important not to be prone to false alarms (which is the worst thing to the user). But it is needed to improve the sensitivity of Delta Dore motion detectors which is not enough to monitor the movements and activities of the inhabitants.

Indeed, the motion detectors need to be sensitive enough to detect movement or changes in the environment. That means it must be possible to detect when people change rooms as this is what e-VITA project is trying to monitor.

As shown in Figure 25, the motion detector is modified to get all starts and ends of detection of the motion detector.

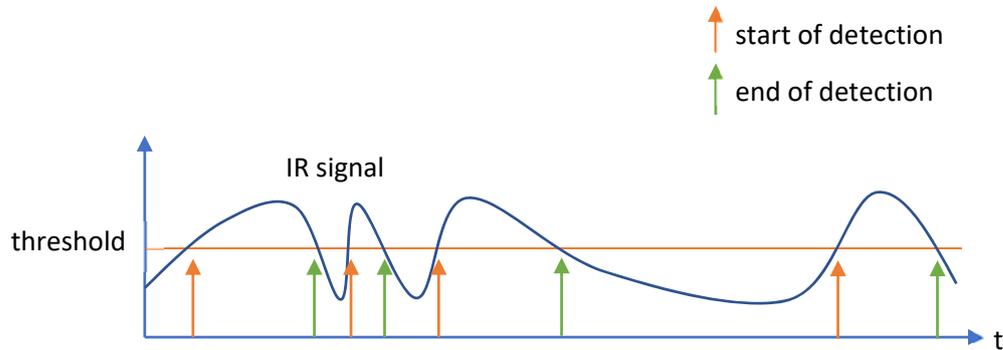


Figure 25 : IR motion detector diagram for eVita

For the e-VITA project, several types of sensors marketed by Delta Dore are of interest to meet the requirements of the project.

Motion detectors can detect the presence of a moving person in a room, which provides information on the occupancy of rooms and the movement of occupants from one room to another. This information can be of interest as a complement to the wearable sensors, especially when they are forgotten or under load. In this case, it is possible to use environmental sensors, especially motion sensors, to infer user activity.

Opening sensors are also a solution to complement wearable sensors and motion sensors, in this case also to infer the movement of occupants in the home. They can be used to detect exits from the home.

This evolution brought to the Delta Dore PIR sensors to improve their sensitivity along the time will allow a better time resolution in the occupants' movements detection, and therefore, a better home areas occupant's localisation labels prediction - such as kitchen, living-room, bedroom, toilets, etc... - performed by the Data Fusion platform (DPF). This latter activity is reported in the deliverable D5.2 on Data Fusion techniques update due at the same period (M24).

3.3.1.1. *Wireless motion detector characteristics*

The technology, the operating and performances of the motion detectors are detailed in the deliverable D4.5 section 4.3.1



Figure 26. DMBD TYXAL+ sensor

Device	DMBD TYXAL+
Manufacturing Company	Delta Dore
Link	https://www.deltadore.fr/domotique/alarme/detecteur/detecteur-mouvement-dmbd-tyxal-plus-ref-6412311
Mechanics & Design	Indoor use Single piece device
Size	H 111 x W 68 x D 54 mm
Compatibility	IP with Tydom Home as gateway
Sensors and measurements	Motion detection: - It transmits detection as soon as the sensor detects movement. End of detection: - It transmits the end of the detection whether there has been no motion detection for 80 seconds.
Detection area	- range: 0.5 to 12 m with standard lens - range: 2 to 10 m with animal immunity lens - aperture angle: 90°
Connectivity	Protocol: X3D Modulation: 2-FSK Frequency: ISM 868.35MHz Data rate: 40 kbps Transmitting power: 1mW(EIRP) Certification standard: CE
Transmission range	300 m in free space
Requirements	Internet connection
Power	Lithium-ion battery
Battery life	10 years
Operating environment	Indoor use Temp: -10°C to +40°C
Free app, lifetime support	Delta Dore free app

Data model	See detail description
-------------------	------------------------

Table 9. DMBD TYXAL+ technical characteristics



Figure 27. DMB TYXAL+ sensor

Device	DMB TYXAL+
Manufacturing Company	Delta Dore
Link	https://www.deltadore.fr/domotique/alarme/detecteur/detecteur-mouvement-tyxal-plus-ref-6412286
Mechanics & Design	Indoor use Single piece device
Size	H 68 x W 77 x D 45 mm
Compatibility	IP with Tydom Home as gateway
Sensors and measurements	Motion detection: - It transmits detection as soon as the sensor detects movement. End of detection: - It transmits the end of the detection whether there has been no motion detection for 10 seconds.
Detection area	- range: 0.5 to 12 m with standard lens - range: 2 to 10 m with animal immunity lens - aperture angle: 90°
Connectivity	Protocol: X3D Modulation: 2-FSK Frequency: ISM 868.35MHz Data rate: 40 kbps Transmitting power: 1mW(EIRP)

	Certification standard: CE
Transmission range	300 m in free space
Requirements	Internet connection
Power	Lithium-ion battery
Battery life	10 years
Operating environment	Indoor use Temp: -10°C to +55°C
Free app, lifetime support	Delta Dore free app
Data model	See detail description

Table 10. DMB TYXAL+ technical characteristics

3.3.1.2. Opening magnetic sensor – Delta Dore DO TYXAL+

The technology, the operating and performances of the motion detectors are detailed in the deliverable D4.5 section 4.3.1.



Figure 28. DO TYXAL+ sensor

Device	DO TYXAL+
Manufacturing Company	Delta Dore
Link	https://www.deltadore.fr/domotique/alarme/detecteur/detecteur-ouverture-bl-tyxal-plus-ref-6412288
Mechanics & Design	Two pieces device Should be installed indoor
Size	H 98 x W 21 x D 25 mm

Compatibility	IP with Tydom Home as gateway
Sensors and measurements	Opening detection - it transmits as soon as there is a change of state (open or closing)
Connectivity	Protocol: X3D Modulation: 2-FSK Frequency: ISM 868.35MHz Data rate: 40 kbps Transmitting power: 1mW(EIRP) Certification standard: CE
Transmission range	300 m in free space
Requirements	Internet connection
Power	Lithium-ion battery
Battery life	10 years
Operating environment	Indoor use Temp: -5°C to +40°C
Free app, lifetime support	Delta Dore free app
Data model	See detail description

Table 11. DO TYXAL+ technical characteristics

3.3.1.3. *Details of the elements for connectivity to the e-VITA platform - Data collection architecture for Delta Dore X3D products*

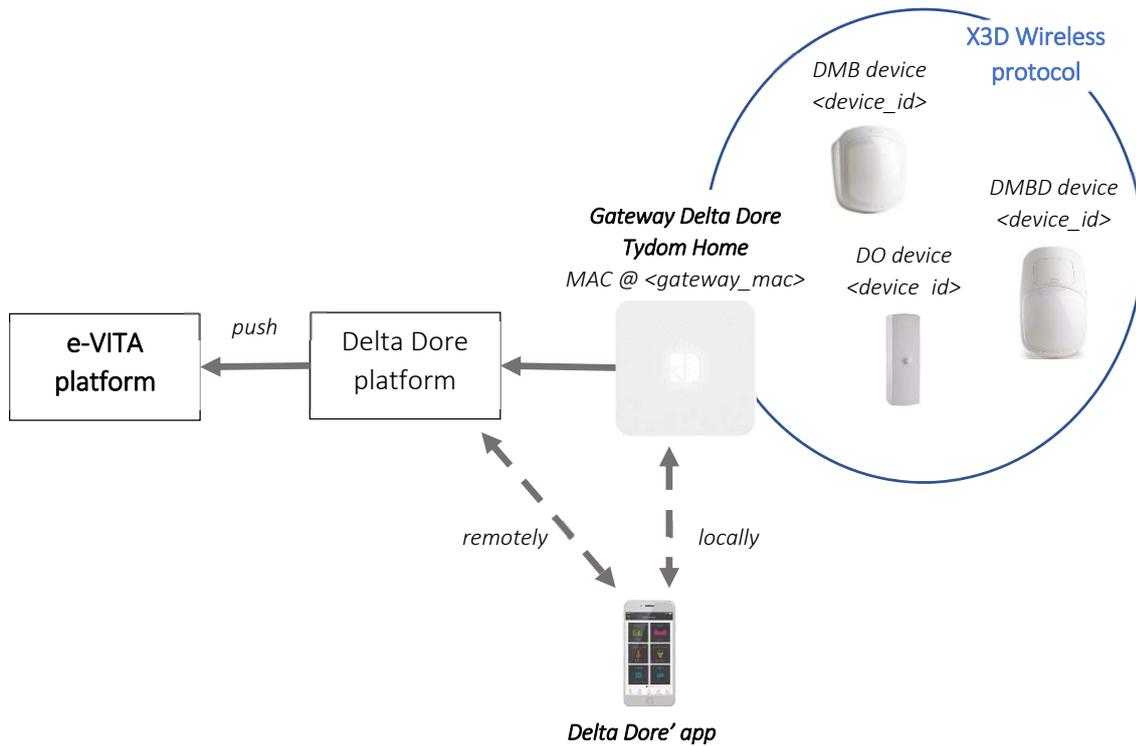


Figure 29. Delta Dore data collection architecture

The Delta Dore devices use the proprietary protocol X3D which is describe in the deliverable 4.5 section 4.3.1.4. This wireless protocol allows to connect the devices to a gateway called Tydom that ensures the connectivity to IP network The Tydom gateway connects natively to the Delta Dore platform, which allows the products to be controlled via the smartphone application available on the stores. There are two modes of connectivity which depend on if the user is in the range of the local network or not.

For e-VITA, the Delta Dore platform pushes the relevant data to the e-VITA platform. This mechanism is done on the Delta Dore platform according to the MAC addresses of the Tydom gateways that are used for e-VITA. For the ADL application, the data pushed to the e-VITA platform is the data from the motion detection and opening detection sensors. A specific application makes it possible to associate these sensors; indeed, in the usual operating context, these sensors cannot be directly used by the gateway. The e-VITA project has therefore enabled the development of a specific application to associate the sensors, as well as the automatic routing of data to the e-VITA platform from the Delta Dore platform.

The API then allows the association of each sensor. The association of the sensors is done in two steps. The first step is to use the API to switch the Tydom Home gateway to association mode and then to associate each sensor in the X3D network by pressing the sensor button. The list of configured sensors can be consulted via the API.

This architecture makes it possible to complete the installation with products by associating these products with the Tydom gateway and to use them with the Delta Dore application while pushing the data that may be useful for the e-VITA use cases.

The data model of the devices is described in the deliverable D4.5 section 4.3.1.6

3.3.2. EnOcean Sensors

In 3.3.1, motion detectors and opening sensors marketed by Delta Dore were introduced as suitable devices for estimating occupant movements. However, these sensors are not available in Japan, so the following EnOcean sensors will be used in the experiments conducted in Japan.

3.3.2.1. Motion sensor - ETC-PIR



Figure 30. EnOcean ETC-PIR

This sensor can be used to detect the presence of people in a room only if they are moving.

The hardware and technical characteristics of the device are listed in Table 12.

Device	EnOcean ETC-PIR
Manufacturing Company	iTEC
Link	https://www.itec-corp.co.jp/index.php?ETC-PIR
Mechanics & Design	Designed for indoor use only
Size	90mm(W) x 35mm(D) x 50mm(H)
Weight	Approx. 60g
Measurement cycle	Human detection signal - Transmit within 3 seconds after detection, or at 1 minute intervals for continuous detection.

	<p>Not detection signal</p> <p>- Transmit within 1 minute after no longer detecting, or at 4-minute intervals for continuous detection.</p>
Connectivity	<p>Protocol: EnOcean (EEP: A5-07-01)</p> <p>Modulation method: FSK</p> <p>Frequency: 928.35MHz</p> <p>Data rate: 125kbps</p> <p>Transmitting power: 1mW (EIRP)</p> <p>Certification standard: ARIB STD T-108</p>
Power	Coin cell battery (CR2450) / Replaceable
Battery life and conditions	10 years (When the room is occupied for 10 hours and absent for 14 hours out of 24 hours)
Detection area	Fan-shaped with a radius of approximately 5 m / 82 degrees up and down / 94 degrees left and right.
Operating environment	<p>Indoor use (no waterproof function)</p> <p>Temp: -5°C to +40°C</p> <p>Humi: 20% to 95% (No condensation)</p>
Transmission distance	150m (under outdoor visibility environment)

<p>Data format</p>	<p>Protocol: EnOcean (EEP: A5-07-01)</p> <table border="1"> <thead> <tr> <th>Offset</th> <th>Size</th> <th>Bitrange</th> <th>Data</th> <th>ShortCut</th> <th>Description</th> <th>Valid Range</th> <th>Scale</th> <th>Unit</th> </tr> </thead> <tbody> <tr> <td>0</td> <td>8</td> <td>DB3.7...DB3.0</td> <td>Supply voltage (OPTIONAL)</td> <td>SVC</td> <td>Supply voltage / super cap. (linear); 251 - 255 reserved for error code</td> <td>0...250</td> <td>0...5.0</td> <td>V</td> </tr> <tr> <td>8</td> <td>8</td> <td>DB2.7...DB2.0</td> <td>Not Used (= 0)</td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td>16</td> <td>8</td> <td>DB1.7...DB1.0</td> <td>PIR Status</td> <td>PIRS</td> <td>PIR Status</td> <td>Enum: 0...127: PIR off 128...255: PIR on</td> <td></td> <td></td> </tr> <tr> <td>24</td> <td>4</td> <td>DB0.7...DB0.4</td> <td>Not Used (= 0)</td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td>28</td> <td>1</td> <td>DB0.3</td> <td>LRN Bit</td> <td>LRNB</td> <td>LRN Bit</td> <td>Enum: 0: Teach-in telegram 1: Data telegram</td> <td></td> <td></td> </tr> <tr> <td>29</td> <td>2</td> <td>DB0.2...DB0.1</td> <td>Not Used (= 0)</td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td>31</td> <td>1</td> <td>DB0.0</td> <td>Supply voltage availability</td> <td>SVA</td> <td>Supply voltage availability at DB_3</td> <td>Enum: 0: Supply voltage is not supported 1: Supply voltage is supported</td> <td></td> <td></td> </tr> </tbody> </table>	Offset	Size	Bitrange	Data	ShortCut	Description	Valid Range	Scale	Unit	0	8	DB3.7...DB3.0	Supply voltage (OPTIONAL)	SVC	Supply voltage / super cap. (linear); 251 - 255 reserved for error code	0...250	0...5.0	V	8	8	DB2.7...DB2.0	Not Used (= 0)						16	8	DB1.7...DB1.0	PIR Status	PIRS	PIR Status	Enum: 0...127: PIR off 128...255: PIR on			24	4	DB0.7...DB0.4	Not Used (= 0)						28	1	DB0.3	LRN Bit	LRNB	LRN Bit	Enum: 0: Teach-in telegram 1: Data telegram			29	2	DB0.2...DB0.1	Not Used (= 0)						31	1	DB0.0	Supply voltage availability	SVA	Supply voltage availability at DB_3	Enum: 0: Supply voltage is not supported 1: Supply voltage is supported		
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28	1	DB0.3	LRN Bit	LRNB	LRN Bit	Enum: 0: Teach-in telegram 1: Data telegram																																																																			
29	2	DB0.2...DB0.1	Not Used (= 0)																																																																						
31	1	DB0.0	Supply voltage availability	SVA	Supply voltage availability at DB_3	Enum: 0: Supply voltage is not supported 1: Supply voltage is supported																																																																			

Table 12. EnOcean ETC-PIR specifications

3.3.2.2. Door sensor - ETB-OCS



Figure 31. EnOcean ETB-OCS

It consists of two parts, one of which is attached to the door or window jamb, this is the active element. The other part is a mechanical part that contains a magnet and is attached to the moving part of the door or window.

These parts are attached to the doors with double-sided tape. The sensor consists of a reed switch on the active element which is closed when the magnetic part is close and opens when the magnet moves away from it, i.e. when the door is open.

The hardware and technical characteristics of the device are listed in Table 13.

Device	EnOcean ETB-OCS
Manufacturing Company	iTEC
Link	https://www.itec-corp.co.jp/index.php?ETx-OCS
Mechanics & Design	Polycarbonate weather-resistant grade material
Water resistance	Equivalent to IPX6
Size	82mm(W) x 24mm(D) x 12mm(H)
Weight	Approx. 22g
Magnet	51mm(W) x 12mm(D) x 7mm(H) / Approx. 6.5g
Measurement cycle	<ul style="list-style-type: none"> - Transmits data the moment it detects the magnet "approaching" or "moving away". - Re-sends the most recent detection results every 30 minutes (for dead-life monitoring).
Connectivity	Protocol: EnOcean (EEP: D5-00-01) Modulation method: FSK Frequency: 928.35MHz Data rate: 125kbps Transmitting power: 1mW(EIRP) Certification standard: ARIB STD T-108
Power	Solar cell

Operating conditions in the dark	24h operation in the dark: 2 hours in 400lx environment 72h operation in the dark: 7 hours in 400lx environment																											
Operating environment	Temp: -20°C to +60°C Humi: 0% to 100% (No condensation)																											
Message content	Digital signal (magnet "approaching"/"moving away" and unique sensor ID)																											
Data format	Protocol: EnOcean (EEP: D5-00-01) <table border="1" data-bbox="491 696 1385 927"> <thead> <tr> <th>Offset</th> <th>Size</th> <th>Bitrange</th> <th>Data</th> <th>ShortCut</th> <th>Description</th> <th>Valid Range</th> <th>Scale</th> <th>Unit</th> </tr> </thead> <tbody> <tr> <td>4</td> <td>1</td> <td>DB0.3</td> <td>Learn Button</td> <td>LRN</td> <td>..</td> <td>Enum: 0: pressed 1: not pressed</td> <td></td> <td></td> </tr> <tr> <td>7</td> <td>1</td> <td>DB0.0</td> <td>Contact</td> <td>CO</td> <td></td> <td>Enum: 0: open 1: closed</td> <td></td> <td></td> </tr> </tbody> </table>	Offset	Size	Bitrange	Data	ShortCut	Description	Valid Range	Scale	Unit	4	1	DB0.3	Learn Button	LRN	..	Enum: 0: pressed 1: not pressed			7	1	DB0.0	Contact	CO		Enum: 0: open 1: closed		
Offset	Size	Bitrange	Data	ShortCut	Description	Valid Range	Scale	Unit																				
4	1	DB0.3	Learn Button	LRN	..	Enum: 0: pressed 1: not pressed																						
7	1	DB0.0	Contact	CO		Enum: 0: open 1: closed																						

Table 13. EnOcean ETB-OCS specifications

3.3.2.3. EnOcean sensors network system

Figure 32 shows an overview of the system that collects the data acquired by the EnOcean sensors introduced in sections 3.2.2.1, 3.3.2.1, and 3.3.2.2 and transmits it to the e-VITA platform.

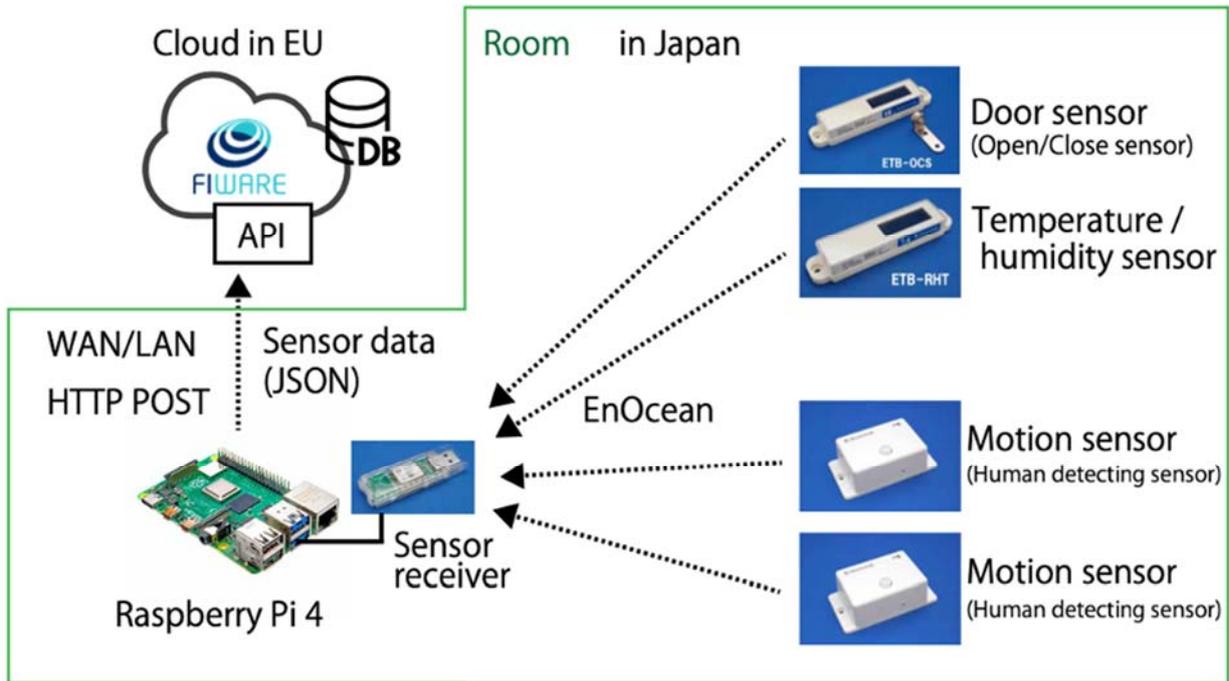


Figure 32. EnOcean sensors network system

As shown in Figure 32, the values from each sensor are collected on a mini-PC (Raspberry Pi 4) with a receiver attached using the EnOcean communication protocol.

The sensor data is then processed into a format (JSON) according to the e-VITA platform (FIWARE) API specification, and the sensor data is sent to the platform using the API.

Upon receiving the sensor data, the e-VITA platform stores the sensor data in a DB.

When sensor data is sent, user IDs are also sent together, and sensor data is stored in the DB with each user distinguished.

4. Smartphone APP

This part deals with the IMT mobile application. The technical aspects related to the development of the application; the different mechanisms allowing data exchanges between the Digital Enabler (DE), the Data Fusion Platform (DFP) and the application; as well as the data catalog of the activity labels will not be treated in this deliverable but in the one on data fusion (D5.2)

The mobile application "MyADL" developed by IMT is closely linked to the work on data fusion. The objective is twofold: on the one hand, to restore these ADLs as simply as possible to the user. On the other hand, to allow the smartphone to communicate the information coming from these embedded sensors in order to valorize them. This valorization allows to make available a high-level information (for example an activity label) to third entities of the e-VITA ecosystem (like the dialogue manager). Moreover, the application allows the smartphone to be used both as a frontend and as a set of sensors.

In order to provide the ADLs, we rely on different sensors of the smartphone. To obtain information on the gait/posture we use the inertial sensors (accelerometer and gyroscope) and the magnetometer. These sensors are an exception to the others because they do not require specific authorization from the user. To obtain information on the positioning we use the GPS. This signal can also give us information on the speed and altitude of the user. Finally, to obtain information on the environment we use microphones. Of course, the GPS and microphone require authorization. In addition, it is possible for each sensor to stop the reading and broadcasting on the DFP. This information can be summarized as follows:

Sensor	Sampling frequency	Sending to DFP frequency
Accelerometer	On change	50 Hz
Gyroscope	On change	50 Hz
User Accelerometer	On change	50 Hz
Magnetometer	On change	50 Hz
GPS	0.1 Hz	0.1 Hz
Microphone	44.1 kHz	-

Table 14. Sampling characteristics of the sensors

To make the application multi-support it has been developed with the flutter framework. In this section we will present the visual rendering of the application. The test run was performed with a Pixel 6 Pro running Android 13. The first visual that is proposed to us is that of the connection. The selection of the "access provider" allows the DFP to determine if the user is internal to the Evident test living lab or if it is an e-VITA user. For all the rest, the data exchanges and the access to the platform are secured. Then we arrive on the home screen which centralizes the information. The navigation tab offers us the possibility to navigate between the following pages:

- Dashboard (Figure 33): Centralizes the data from the on-board sensors in graphical form.
- Status & Settings: Centralizes all the commands of the different sensors.
- Mapper: Uses the GPS location to indicate the user's position on the map.

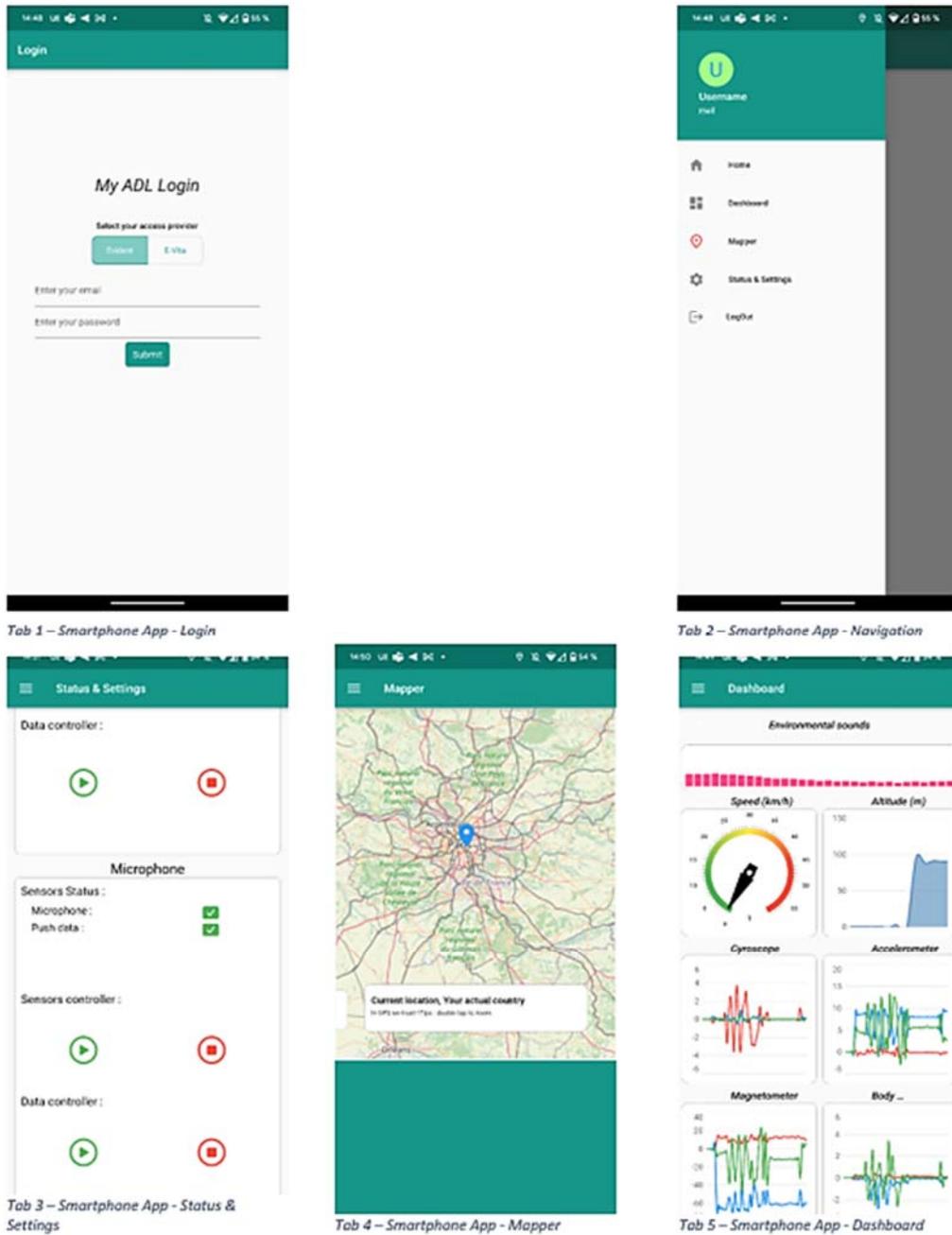


Figure 33. ADL application windows

5. Optimization of the Home Sensor Network for Monitoring Older People

The sensor network making up the e-VITA platform that is installed in the home of the end-user depends on the preferences and needs of the latter. Identifying the optimal configuration of the sensor network is the task of the Use Cases Configurator, a software component developed by T4.2 (description in D4.3) that, focusing on creating an intelligent living environment suitable for the older adult, considers in addition to user preferences also the minimization of costs and the number of sensors without losing the accuracy of the measurement. In this way, the users have a service tailored to their needs and preferences to avoid negative feedback. The analysis of the technical characteristics (detection area, accuracy, sensitivity, etc.) of the sensors of the e-VITA platform has been carried out by T4.3, also responsible for testing the sensors to optimize their installation inside the end-user home.

The UNIVPM research team developed a methodology to optimize the home sensor network to measure the Activities of Daily Living (ADLs) of older people using Machine Learning (ML) applied to synthetic data generated via a Smart Living Environment (SLE) simulation tool [26] developed in the framework of the eWare project. A home sensor network consisting of Passive InfraRed (PIR) and door sensors allows people to age in place avoiding invasiveness of the technology by keeping track of the older users' behaviour and health conditions. However, it is difficult to identify a priori the optimal sensor network configuration to measure users' behaviour. To ensure better user acceptability without losing measurement accuracy, the proposed methodology allows to optimize the home sensor network by simulating human activities, and therefore sensor activations, in the reconstructed environment and analysing the datasets generated through ML.

It is possible to monitor the user's behaviour without contact in the living environment and predict well-being by identifying ad hoc services [27]. Keeping track of the users' behaviour, by classifying and recognizing Activities of Daily Living (ADLs), and health conditions avoiding invasiveness of the technology [28,29], travels, and visits to hospital and care centers, especially in a pandemic emergency, like COVID-19 [21], has become a necessity. In this context, a smart living environment (SLE) characterized by IoT-connected devices [30] allows people to age in place and live longer, while reducing costs for care systems [31].

Realizing an appropriate SLE characterized by a non-invasive home sensor network for measuring the measuring the behaviour [32] and health conditions [33] of older people is the goal of e-VITA project. A home sensor network made up of Passive InfraRed (PIR) and door sensors meets the aforementioned requirements for monitoring users' behaviour within their home, which is why it is one of the most used type of sensor network in the monitoring field of ageing in place [27,34–38].

The problem is that different configurations of the home sensor network affect data output, i.e. the measurement of ADLs. Thus, a system architect must choose the right approach to design the sensor network, verifying if additional sensors or different positions would improve or impair the desired result. This decision must be settled before the sensors are installed. At this stage, datasets representative of users' activities and sensors activations are necessary to develop ML models to classify ADLs. Two are the main approaches to obtain test data. One is to generate real data in a laboratory where the smart home is reproduced. This solution is good but costly and time-consuming.

Additionally, when creating real smart home test beds, it is important to have a robust and continuous system to capture sensors’ data and an appropriate method to take note of user’s activities. The other approach consists in generating synthetic data using tools able of simulating the home environment, the sensors installed in it, and the activities of the users. These tools overcome the drawbacks of creating real datasets, simplifying fast data generation, and offering robust methods to obtain sensors’ data, but most of them are not open-access and are limited to specific sensors which do not match the purpose of measuring users’ ADLs. Thus, we developed a SLE simulation tool to simulate human activities and sensors activations in the reconstructed environment. The tool has been designed based on the hybrid approach described in the literature [39], which combines [40] the model-based approach [41] that facilitates data generation, and the interactive approach [42] that uses virtual environments and sensors responding to user interaction. The SLE simulation tool is used to simulate indoor human trajectories, starting from the home environment, the number and characteristics of the simulated PIR and door sensors and the user’s profile. The generated datasets are subsequently fed to ML algorithms to classify user’s ADLs. Therefore, the optimal configuration of the home sensor network is identified by analyzing the accuracy achieved in ADLs classification and the implementation costs (Figure 34).

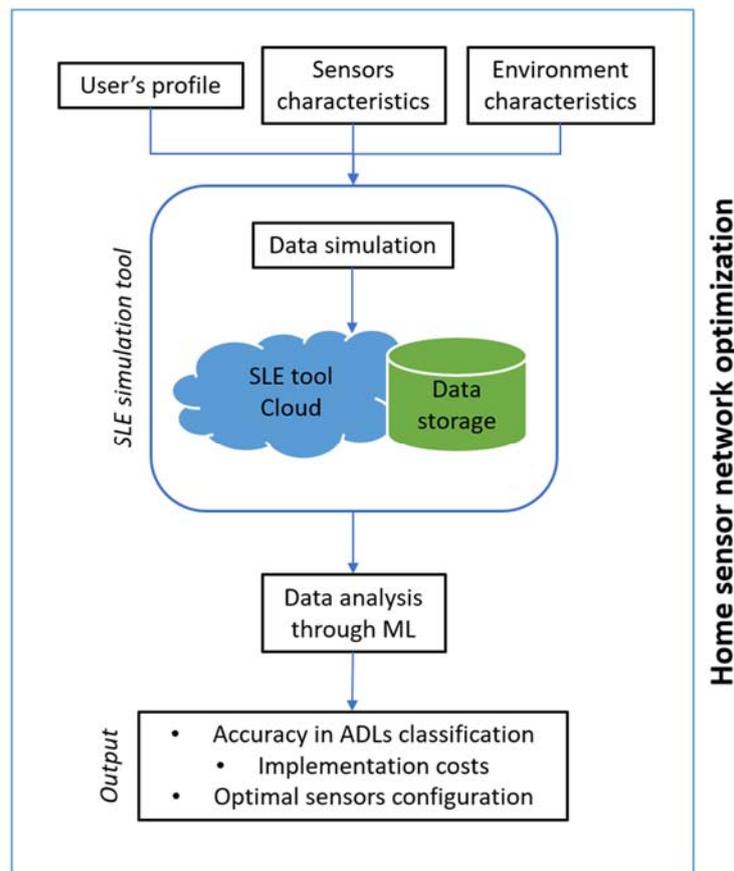


Figure 34. Conceptualization of the home sensors network optimization method.

5.1. Related Work

Literature research showed how much effort has been done in generating datasets for smart home applications. These datasets are created using real smart home test beds, a costly and time-consuming process, or simulation tools, which allow fast and easy data generation. During the research we focused on investigating different tools for reproducing the smart home and simulating sensors in the environment. These tools are mainly categorized into model-based and interactive approaches and can be based on both 3D and 2D models.

The model-based approach [41] facilitates the generation of synthetic data using pre-defined activity models, defining the order of events, the probability of their occurrence and the time spent for each event during the execution of activities. The model-based approach [43,44] enables data generation for extended periods. To simulate a significant amount of data, the user must script each day independently. This is one of the main drawbacks of using these simulators in healthcare applications since several weeks of data are required to capture long-term behavioral models. Another problematic aspect is the design and description of a complex activity model that needs access to real test data containing all the intrinsic aspects that characterized such activities. The advantage of the model-based approach is instead the simulation of activities related to sensors activation associated with specific rooms of the smart home. The PerSim 3D tool [43] allows to define contexts and to set sensors' values ranges for generating datasets from inhabitant's activities, which are visualized through a 3D interface. However, this tool is not publicly accessible. Another 3D smart home simulator is SIMACT [45]. This tool has a series of pre-stored scenarios created from data collected from medical studies, which can be used to generate datasets for activity recognition. CASS [46] is a 2D context-aware simulation tool that generates information related to with virtual sensors and devices. The user can establish the appropriate sensors and devices for the smart home by identifying conflicts of rules in context information. Caruso et al. [47] developed a simulator using process declaration models for modeling the habits performed by the virtual resident. The authors showed how different sensor configurations generate different sensory registers that can be employed as input for activity recognition techniques to provide guidelines for setting up a sensor network for the real smart home.

Most of these tools that used the interactive approach focus on providing a first-person, third-person or overhead view of the environment. The approach facilitates the adjustment of sensor properties but does not provide the output of sensors commonly used to recognize ADLs. On the other hand, the interactive approach uses virtual environments and sensors responding to user interaction. In this case, the user can move the virtual inhabitant inside the recreated smart home allowing it to interact with the environment. The interaction can be both active (e.g., turning on/off the light) and passive (e.g., the PIR sensor activation following the detection of virtual inhabitant movement in its measuring range). This approach has the disadvantage to take a long time to generate datasets, since the interactions are collected in real-time. Buchmayr et al. [48] developed a simulator that models binary and temperature sensors. The simulator models the behaviour of defective sensor by confusing the sensor reading with a noise signal. The simulator needs user interaction to produce sensor readings by pressing on them. However, this approach is challenging in the case of numerous sensors, in particular in scenarios where multiple sensors need to be activated at the same time. Synnott et al. [49] presented a tool that allows users to create a simulated smart home providing a 2D view of the floorplan within which it is possible to perform ADLs via a virtual avatar. This tool has been shown to ease datasets

generation that capture the performance of normal and abnormal activities, like dangerous scenarios, but is not available in the public domain. The smart home simulation tool developed by Ariani et al. [50] provides a 2D map editor to create a floorplan and to add ambient sensors: it simulates binary motion sensors activations at the inhabitant's movements. Nishikawa et al. [51] proposed UbiREAL, a simulation tool that integrates a 3D interface to reproduce the implementation of the sensors, which simulates communication between them and reproduces the variation of physical quantities (e.g., temperature, humidity) caused by the devices (e.g., air conditioners).

This research found that the model-based approaches allow the generation of huge datasets in short times, but at the expense of accuracy in catching realistic interactions. Interactive approaches, instead, can reproduce realistic simulations, but they take longer. Therefore, the developed SLE simulation tool has been designed based on the hybrid approach described by Alshammari et al. [39] which, bringing together model-based and interactive approaches advantages, resulted in the OpenSHS 3D smart home simulator. This tool offers the possibility to generate datasets in a short time, since starting from a produced small sample, this can be increased with no impact on the sequence of events.

The UNIVPM group's first experience of development of the SLE simulation tool to optimize sensor networks for the measurement of user's ADLs is reported in [52]. In this previous work, the SLE simulation tool realized using Matlab has been used to generate normal and wandering trajectories and the associated activations of the sensors. The simulated data have been trained with ML algorithms to identify overnight wandering. The results proved that the Decision Tree (DT) algorithm is reliable in discriminating between normal and wandering trajectories measured by PIR sensors, achieving 95% accuracy using a cross-validation method. After this experience, we improved the tool including more complex aspects, e.g., adding the parametrization of sensors and environment, the daily time, and a function to create perturbation in the daily activities between a simulation day and others. Furthermore, the software has been modified using a web-application software [53].

5.2. Smart Living Environment Simulation Tool

The SLE simulation tool, developed using the open-source Zend framework, considers the user's profile, the environment, and sensors characteristics, to provide a PIR and door sensors activations dataset from simulated virtual user trajectories. By analyzing the accuracy of user's ADLs classification using ML algorithms, it is possible to optimize the home sensor network in the reconstructed environment by changing its configuration.

5.2.1. User's profile

The analysis of the user's profile defines the useful ADLs for the measurement. Based on the use case, therefore, a service tailored to the user's needs and preferences must be created to avoid negative feedback. Optimizing the sensors network installed in the user home, which means trying to minimize the number of sensors and install them in optimal locations without losing measurement accuracy, will bring a reduction of costs and a better user acceptance.

5.2.2. Environment characteristics

The first approach with the tool is the uploading of the environment map. When the house map is uploaded, the rooms are selected by defining their boundaries and assigning a label to each of them, e.g., bedroom, kitchen, etc. The apartment shown as ex-ample in Figure 35 consists of a kitchen, a living room, a hallway, a hobby room, a toilet, a bedroom, and a garage. The function to parameterize the 2D environment is described in (1):

$$F_{ENV}(x, y) = f(X_r, Y_r, N_r, N_d, N_o, A) \quad (1)$$

where X_r, Y_r consider the geometry of the room, the variables N_r, N_d, N_o indicate the number of rooms, doors and obstacles respectively, and A is the walking area in square meters. Since these parameters influence the measurement in several ways, we added a quantity named the uncertainty of the environment Δ_E , which represents their spatial (coordinates (x, y)) and temporal (t) variability in the recreated space. By changing, for example, the number of obstacles over time (new obstacle with position (x, y) introduced at time (t)), Δ_E will account for the resulting change in the walking area. The function that describes the problem considering the time (t) becomes, (2):

$$F(x, y, t) = F_{ENV}(x, y, t) = f(X_r, Y_r, N_r, N_d, N_o, A) + \Delta_E(x, y, t) \quad (2)$$

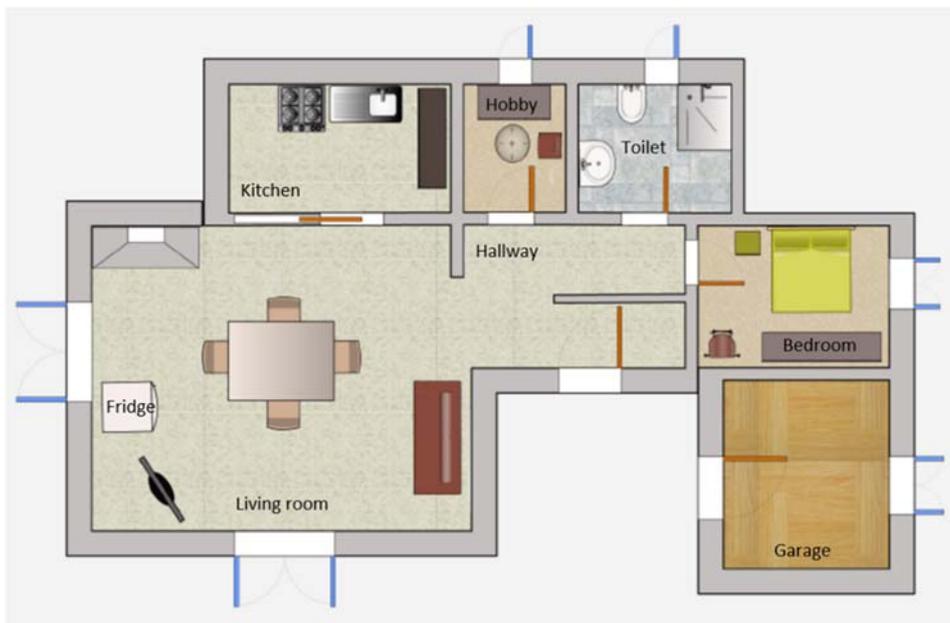


Figure 35. Example of a 2D apartment map uploaded in the SLE simulation tool.

5.2.3. Sensors' characteristics

After the identification of the rooms, the PIR and door sensors' characteristics are entered in the tool: the field of view FoV (degrees), detection range R (m) and time delay Td (s). These parameters are fully customizable by the user. In the simulation scenarios taken as case studies, we referred to the characteristics of the Delta Dore DMB Tyxal+ PIR sensor (cost 150 €) with FoV=90°, R=10 m, and Td=10

s, and the Delta Dore DO BL Tyxal+ door sensor (cost 100 €) with $T_d=10$ s. At this point, the sensors are positioned in the rooms. In the simulation tool, the PIR sensors are wall-mounted at a height of 1.40 m from the floor.

The sensors are parameterized following (3) and (4):

$$F_{PIR_n}(x, y, t) = f(FOV, R, Td) + \Delta_{PIR}(x, y, t) \quad (3)$$

$$F_{DOOR_n}(x, y, t) = f(Td) + \Delta_{DOOR}(x, y, t) \quad (4)$$

Therefore,

$$F_{SENSORS}(x, y, t) = \sum_1^n F_{PIR_n}(x, y, t) + \sum_1^n F_{DOOR_n}(x, y, t) \quad (5)$$

where n is the n th PIR or door sensor, so $F_{SENSORS}$ is the function that describes the characteristics of the sensors and considers the uncertainties Δ_{PIR} and Δ_{DOOR} related to the variability of sensors' position (x, y) in the recreated environment at time (t) that creates changes in the measurement of movement or door opening/closing.

According to these considerations, the (2) becomes (6):

$$F(x, y, t) = F_{ENV}(x, y, t) + F_{SENSORS}(x, y, t) \quad (6)$$

5.2.4. Data simulation

After the sensors and environment have been set up, the simulation can begin. The virtual user's behaviour is defined by the execution of activities, which are simulated by drawing trajectories by moving the mouse cursor from one room to another, making trajectories that may or may not be within the detection range of the sensors, Figure 36. Entering in the PIR sensor detection range, the state of the sensor automatically turns from OFF to ON and remains so until the user is no longer intercepted. The door sensor, on the other hand, passes from the OFF to ON state when the traced trajectory overlaps its detection range, stopping for a certain amount of time (mimicking the opening/closing of a door), and then returns to the OFF state as the trajectory moves away.

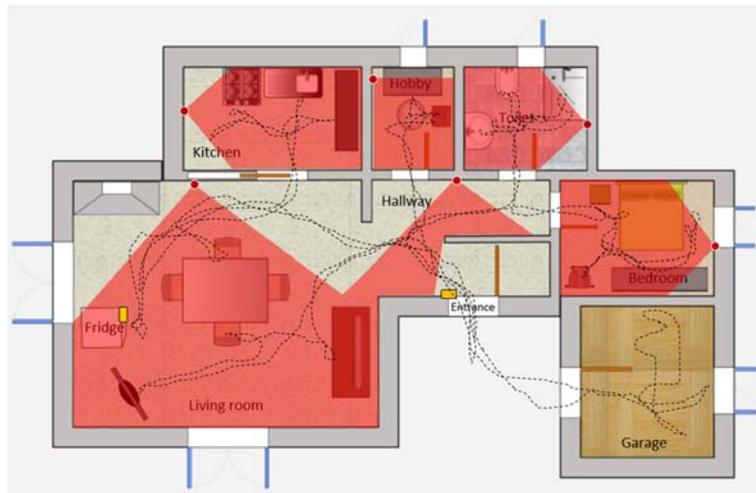


Figure 36. Example of virtual user trajectories (dashed line), PIR sensors (red points) with their detection ranges (red areas), and door sensors (yellow rectangles).

A geo-localization function is integrated into the tool to determine the position of the user in the environment based on the activated sensor. At the end of the simulation, the trajectories detected by the sensor network constitute the generated data that can be saved in a .txt file, Figure 37. The tool also includes a function to speed up the simulation time of the virtual user activities.

TIMESTAMP	SENSOR
2022-07-14 07:17:56	pir_HALLWAY ON
2022-07-14 07:18:47	pir_HALLWAY OFF
2022-07-14 07:18:47	pir_TOILET ON
2022-07-14 07:28:30	pir_TOILET OFF
2022-07-14 07:28:30	pir_HALLWAY ON
2022-07-14 07:29:25	pir_HALLWAY OFF
2022-07-14 07:29:25	pir_LIVINGROOM ON
2022-07-14 07:31:42	pir_LIVINGROOM OFF
2022-07-14 07:31:42	pir_KITCHEN ON
2022-07-14 07:32:50	door_FRIDGE ON
2022-07-14 07:33:28	door_FRIDGE OFF
2022-07-14 07:42:15	pir_KITCHEN OFF
2022-07-14 07:42:15	pir_HALLWAY ON
2022-07-14 07:43:06	pir_HALLWAY OFF
2022-07-14 07:43:06	door_ENTRANCE ON
2022-07-14 07:43:14	door_ENTRANCE OFF

Figure 37. Example of data generated by the SLE tool and saved in the .txt file. The activation (ON) and deactivation (OFF) timestamp of the sensors following the user simulated movement or interaction is captured at the moment of the action.

The first day of data is simulated manually within the tool. To speed up the achievement of a large dataset, an automatic perturbation has been implemented: after importing the .txt file via a calendar view, the simulated data of a chosen day can be copied to a new one with a perturbation consisting in the introduction of a random shift of the time (some minutes) and sensor state. Thus, it is possible to automatically generate numerous months of simulated sensors activations with just one click of the mouse.

5.2.5. ADLs classification and evaluation metric

Once the physical aspects are identified, i.e., environment and sensors parameterization, the simulated data are used to classify user’s ADLs through four supervised ML algorithms: Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Gaussian Naive Bayes (GNB). This choice was determined by the broad use of these algorithms in this context, given their high accuracy. In particular, many studies have shown that these algorithms perform well in classifying ADLs, revealing a good stability and simplicity of implementation and interpretation [54], [55], [56]. Furthermore, we decided to use different algorithms in order to compare their performance and determine which one would be most suitable to refer to during the optimization of the sensor network. Table 15 shows the hyperparameter selected for each of the used ML algorithm.

ML Algorithm	Hyperparameter	Value
DT	Criterion	Gini
	Min samples split	2
	Min samples leaf	1
	Max depth	None
SVM	C	1

	Kernel	rbf
	Gamma	1/n° features
K-NN	n° of nearest neighbors	3
GNB	No parameter	-

Table 15. Hyperparameters selected for the Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Gaussian Naïve Bayes (GNB) algorithms.

Accuracy (7), recall (8), precision (9) and F1-score (10) of ADLs classification were computed using hold-out validation, splitting the data into training set (70%) and testing set (30%). In addition, a 10-Fold Cross Validation (CV) was performed on the dataset and the mean values of accuracy (7), recall (8), precision (9) and F1-score (10) of ADLs classification over the splits were calculated.

$$Accuracy [\%] = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (7)$$

$$Recall [\%] = \frac{TP}{TP+FN} \times 100\% \quad (8)$$

$$Precision [\%] = \frac{TP}{TP+FP} \times 100\% \quad (9)$$

$$F1 \text{ score} [\%] = 2 * \frac{Recall*Precision}{Recall+Precision} \times 100\% \quad (10)$$

where TP = True Positives, TN= True Negatives, FP = False Positives, and FN = False Negatives.

The goal of the ML algorithms is to classify with a certain accuracy the ADLs carried out by the user using different sensors' layouts of the same apartment. Each algorithm was trained following (i) sensors-based models [57], (ii) interpretation and fusion of sensors data, (iii) identification of basic actions and (iv) activity recognition [58]. The decision of using several types of ML algorithms lay in the need to identify which of them would perform best in activity recognition. The key benefit of ML analysis consists in the possibility to perform a simulation based on a specific environment and sensor configuration and, according to the result, to test various configurations in order to optimize the sensor network, obtaining the most suitable compromise between accuracy of ADLs classification, user acceptability and implementation costs.

In the process of optimizing the home sensor network, two different apartments were considered as case studies, whose ADLs classification accuracy of ML algorithms and cost were examined while changing the sensor network layout: a large apartment with many rooms (Case Study 1), and a small apartment with few rooms (Case Study 2), Figure 38.



Figure 38. Map of the apartments of Case Study 1 (a) and Case Study 2 (b).

For each of them, 6 months of activities of an older user were simulated using the SLE tool for three different configurations of the home sensor network. The ML algorithms' ability to classify the following ADLs from the simulated user trajectories for Case Study 1 was tested: breakfast, lunch, dinner, cooking, ambulating, sleeping, dressing, go to the toilet/personal hygiene, entering/leaving, having a hobby, relaxing/watching TV. For Case Study 2 the defined ADLs to be measured were the following: breakfast, lunch, dinner, cooking, ambulating, sleeping, dressing, go to the toilet/personal hygiene, entering/leaving.

5.2.6. Case Study 1

The first SLE reported in this study is a seven-room European-style apartment. As a starting configuration, 5 PIR sensors are installed: one in the hallway, one in the bedroom, one in the toilet, one in the hobby room and one in the living room. Furthermore, 2 door sensors are installed: one on the fridge door and one on the entrance door, Figure 39.



Figure 39. The first configuration of the home sensor network of Case Study 1.

The SLE tool offers a graphical representation of the simulated sensors activations data. Figure 40 shows as an example the graph of the 6 months of simulated data for the first home sensor network configuration of Case Study 1.

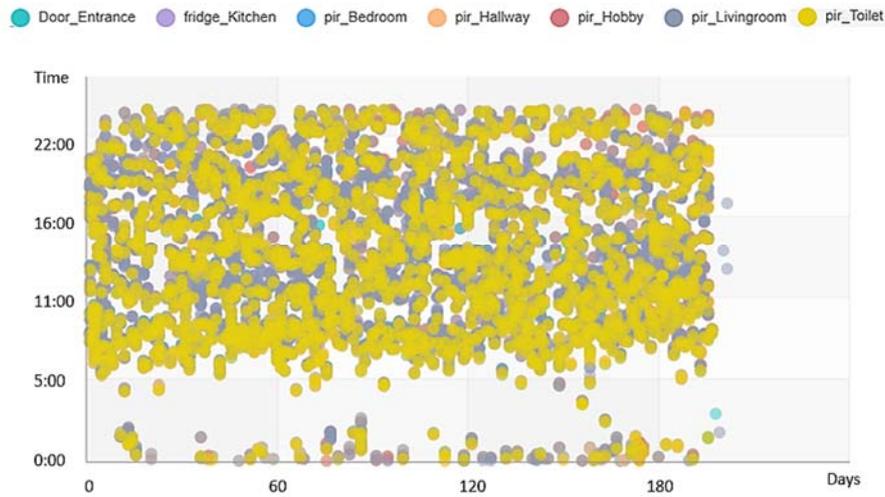


Figure 40. Graphical representation of the SLE tool of the simulated PIR and door sensors activations for the first home sensor network configuration of Case Study 1. Each colored dot represents the activity detected by the related sensor (the legend indicates the colors associated with the sensors) in a given day and time.

The second configuration, Figure 41, considers 6 PIR sensors, adding to the previous configuration one PIR sensor in the kitchen and removing the door sensor from the fridge.



Figure 41. The second configuration of the home sensor network of Case Study 1.

The SLE tool also offers a statistical analysis area in which the time spent in each room (in seconds) and the number of sensors activations per each room/door for the simulated datasets are reported. Figure 42 shows as an example the graphs related to the analysis of the 6 months of simulated data for the second home sensor network configuration of Case Study 1.

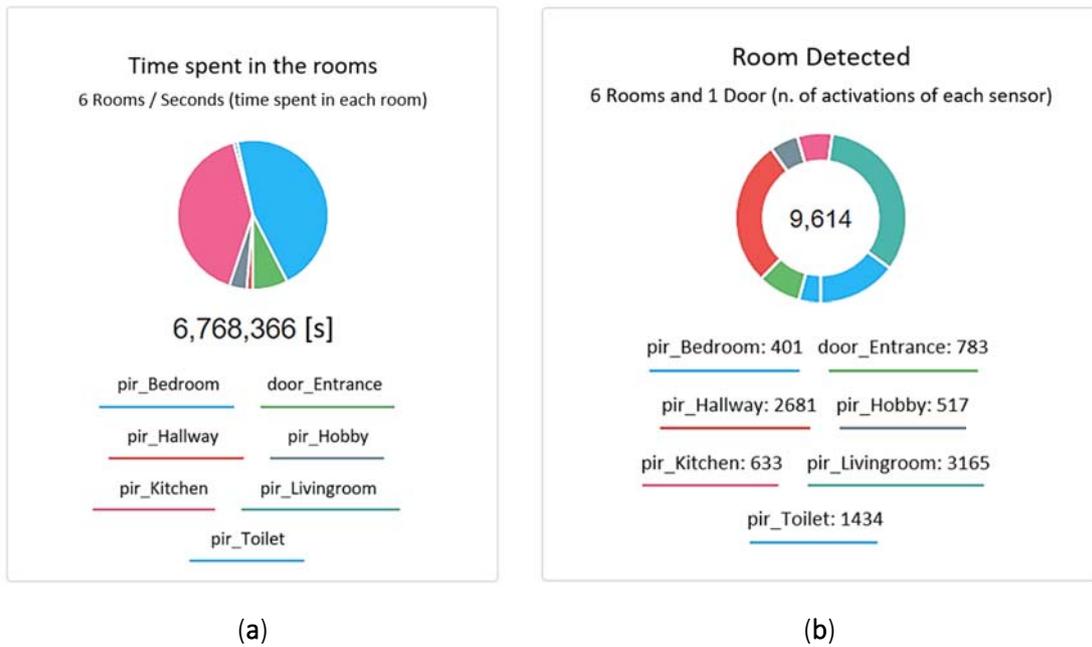


Figure 42. Graphical representation of the statistical analysis of the SLE tool for the simulated PIR and door sensors activations for the second home sensor network configuration of Case Study 1. (a) Time spent in each room in seconds; (b) Number of PIR and door sensors activations.

The third configuration, Figure 43, considers 5 PIR sensors and one door sensor on the entrance door, removing to the previous configuration the PIR sensor in the bedroom.



Figure 43. The third configuration of the home sensor network of Case Study 1.

5.2.7. Case Study 2

The second SLE reported in this study is a small three-room Japanese-style apartment with. As a starting configuration, 3 PIR sensors are installed: one in the toilet, one in the bedroom and one in the kitchen, Figure 44.



Figure 44. The first configuration of the home sensors network of Case Study 2.

The second configuration, Figure 45, considers only 2 PIR sensors, removing from the previous configuration the PIR sensor in the bedroom.



Figure 45. The second configuration of the home sensors network of Case Study 2.

The third configuration, Figure 46, adds to the second configuration a door sensor installed on the entrance door.



Figure 46. The third configuration of the home sensors network of Case Study 2.

To summarize, the method proposed consists of the following steps:

- Identify which are the relevant ADLs to be measured for the older user.
- Design different configurations of the home sensor network and recreate them in the SLE simulator.
- Simulate the behaviour of the older user via the SLE tool to generate a consistent dataset of sensors activations.
- Analyze the obtained dataset through ML algorithms and evaluate which configuration best measures the user’s ADLs (highest accuracy in ADLs classification).
- Finally, the optimization of the home sensor network configuration is given by a cost-effectiveness analysis, in terms of ADLs classification accuracy and cost of the installed sensor network.

5.3. Simulation Results

The results of the hold-out validation and 10-Fold CV, considering as input the simulated 6-months datasets generated, are reported as values of the aforementioned evaluation metric. The performance of the four ML algorithms, considering the three different home sensor network configurations in the SLE of Case Study 1, for hold-out validation are shown in Table 16 while for 10-Fold CV are shown in Table 17. Table 18 instead shows the estimated cost of the different network configurations of Case Study 1.

Configurations	ML Algorithms	Precision [%]	Recall [%]	F1-score [%]	Accuracy [%]
1	DT	98	98	98	98
	SVM	11	34	50	34
	KNN	85	81	82	81
	GNB	11	32	50	32
2	DT	99	99	99	99
	SVM	15	38	56	38
	KNN	58	76	87	76
	GNB	92	95	98	95
3	DT	98	98	98	98
	SVM	15	39	56	38
	KNN	36	52	45	52
	GNB	87	88	89	89

Table 16. Percentage values of precision, recall, F1-score and accuracy of the Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Gaussian Naïve Bayes (GNB) algorithms in classifying user’s ADLs for hold-out validation for the three home sensors network configurations of Case Study 1.

Configurations	ML Algorithms	Precision [%]	Recall [%]	F1-score [%]	Accuracy [%]
1	DT	94	90	90	99
	SVM	4	11	7	34
	KNN	70	69	66	94
	GNB	25	31	37	34
2	DT	99	99	99	99
	SVM	4	11	6	38
	KNN	70	70	69	93
	GNB	74	79	76	95
3	DT	99	99	99	99
	SVM	40	6	8	40
	KNN	80	80	79	97
	GNB	82	86	83	90

Table 17. Mean percentage values over the splits of precision, recall, F1-score and accuracy of the Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Gaussian Naïve Bayes (GNB) algorithms in classifying user's ADLs for 10-Fold CV for the three home sensors network configurations of Case Study 1.

Configurations	Cost [€]
1	900
2	1000
3	850

Table 18. Cost of the different home sensor network configurations of Case Study 1.

The mean accuracies over the three home sensor network configurations of Case Study 1 achieved by the four ML algorithms for hold-out validation and 10-Fold CV were computed to identify which of them was the best suited for classifying ADLs, Figure 47.

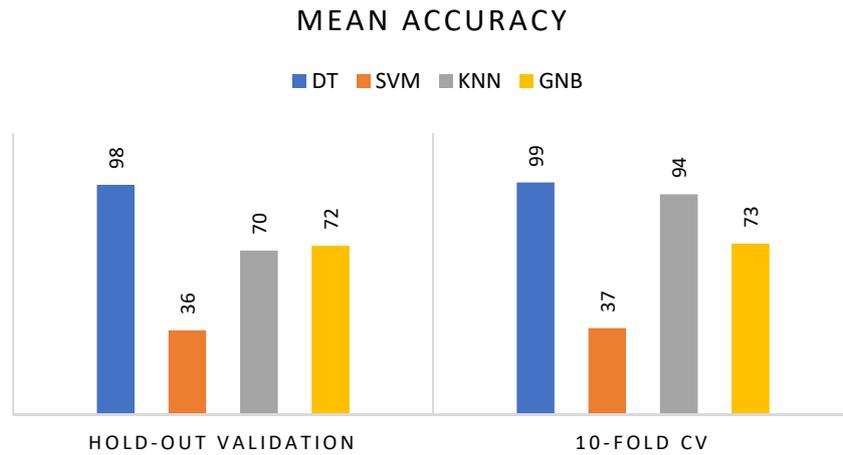


Figure 47. Mean accuracy achieved by the DT, KNN, SVM, GNB classifiers over the three home sensor network configurations of Case Study 1 for hold-out validation and 10-Fold CV.

The performance of the four ML algorithms, considering the three different home sensor network configurations in the SLE of Case Study 2, for the hold-out validation are shown in Table 19 while for the 10-Fold CV in Table 20. Table 21 instead shows the estimated cost of the different network configurations of Case Study 2.

Configurations	ML Algorithms	Precision [%]	Recall [%]	F1-score [%]	Accuracy [%]
1	DT	98	98	98	98
	SVM	10	31	48	31
	K-NN	45	64	81	64
	GNB	37	56	77	56
2	DT	91	91	91	91
	SVM	24	49	59	49
	K-NN	79	80	79	80
	GNB	48	50	54	50
3	DT	93	94	94	94
	SVM	15	39	56	39
	K-NN	46	65	81	65
	GNB	56	61	93	61

Table 19. Percentage values of precision, recall, F1-score and accuracy of the Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Gaussian Naïve Bayes (GNB) algorithms in classifying user's ADLs for hold-out validation for the three home sensors network configurations of Case Study 2.

Configurations	ML	Precision [%]	Recall [%]	F1-score [%]	Accuracy [%]
	Algorithms				
1	DT	94	94	94	97
	SVM	6	2	9	30
	KNN	56	56	53	63
	GNB	46	60	51	69
2	DT	93	91	92	91
	SVM	25	50	33	50
	KNN	60	75	83	80
	GNB	43	57	53	51
3	DT	83	82	81	94
	SVM	10	25	14	37
	KNN	71	70	68	82
	GNB	72	75	73	73

Table 20. Mean percentage values over the splits of precision, recall, F1-score and accuracy of the Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Gaussian Naïve Bayes (GNB) algorithms in classifying user's ADLs for 10-Fold CV for the three home sensors network configurations of Case Study 2.

Configurations	Cost [€]
1	450
2	300
3	400

Table 21. Cost of the different home sensor network configurations of Case Study 2.

Figure 48 shows the mean accuracies over the three home sensor network configurations of Case Study 2 achieved by the four ML algorithms for hold-out validation and 10-Fold CV were computed to identify which of them was the best suited for classifying ADLs.

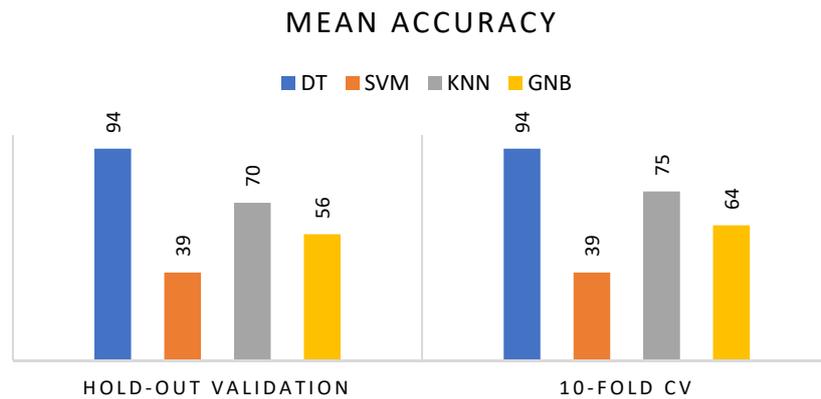


Figure 48. Mean accuracy achieved by the DT, KNN, SVM, GNB classifiers over the three home sensor network configurations of Case Study 2 for hold-out validation and 10-Fold CV.

5.4. Discussions

We assessed the accuracy of different home sensor network configurations in measuring specific ADLs using four different ML algorithms (i.e., DT, SVM, KNN, GNB). We used different algorithms in order to compare their performance and determine which one would be most suitable to refer to during the optimization process of the home sensor network.

We realized that in real scenarios it is always difficult to design a correct configuration of PIR and door sensors to measure older people’s ADLs due to the different characteristics of users and apartments. Considering the scenarios used for this study, we identified that it was important for the older users to keep track of sleep patterns, eating activities (breakfast, lunch, dinner, cooking), personal hygiene activities (going to the toilet) and activities related to staying active and engaged in recreational activities (ambulating, dressing, entering/leaving, having a hobby, relaxing/watching TV). For each case study, three different home sensor network configurations were designed and 6 months of activity by an older virtual user were then simulated using the SLE tool, to generate datasets consisting of home sensor network activations.

The performance of the four ML algorithms tested on the generated datasets in terms of ADLs classification accuracy, precision, F1-score and recall, considering the three different home sensors network configurations of Case Study 1 and Case Study 2, for hold-out validation are shown in Table 16 and Table 19 respectively. Each algorithm has been trained on 70% of the generated 6-month datasets and tested on the remaining 30%. Table 17 and Table 20 show instead the ADLs classification accuracy of the ML algorithms for 10-Fold CV considering the three home sensor network configurations of Case Study 1 and Case Study 2 respectively. Considering the measured accuracies as a comparison term, the results show that for Case Study 1 the DT classifier achieved the highest accuracy in classifying the user’s ADLs for both hold-out validation (98%) and 10-Fold CV (99%). The mean accuracy achieved by the DT, KNN, SVM, GNB classifiers over the three home sensor network configurations of Case Study 1 (Figure 47) proved that the DT classifier is the most suitable in classifying ADLs with 98% mean accuracy for hold-out validation and 99% mean accuracy for 10-Fold CV, compared to SVM (36% mean accuracy for hold-out validation and 37% mean accuracy for 10-Fold CV), KNN (70% mean accuracy for hold-out validation and 94% mean accuracy for 10-Fold CV), and GNB (72% mean accuracy for hold-out validation

and 73% mean accuracy for 10-Fold CV). The results for Case Study 2 also show that the DT classifier achieved the highest accuracy in classifying user's ADLs (over 91% for both hold-out validation and 10-Fold CV). In fact, the mean accuracy over the three home sensor network configurations of Case Study 2 achieved by the ML algorithms (Figure 48) proved also in this case that the DT classifier is the most suitable in classifying ADLs with 94% mean accuracy for both hold-out validation and 10-Fold CV, compared to SVM (39% mean accuracy for hold-out validation and 39% mean accuracy for 10-Fold CV), KNN (70% mean accuracy for hold-out validation and 75% mean accuracy for 10-Fold CV), and GNB (56% mean accuracy for hold-out validation and 60% mean accuracy for 10-Fold CV). In the optimization process, therefore, the comparison between the sensor networks' capabilities in the measurement of ADLs was carried out based on the accuracy achieved by the DT algorithm. In addition to being one of the most used supervised classification algorithms [54–56], DT requires no pre-processing actions and needs less time to process data than other algorithms. It provides a good forecast for datasets consisting of simple features, like our case, as opposed to SVM, which performs well on big and intricate datasets. Furthermore, as reported in [59] and [60], DT proves to be more accurate than KNN and GNB in classification problems. However, the problem of overfitting can affect such ML classifier. There are specific techniques to mitigate it and one of them is to perform a k-Fold CV on the dataset, which is also helpful in assessing the performance of ML models. In this study, we performed a 10-Fold CV on the dataset, which means that the ML algorithms divided the data into 10 parts to execute the adaptation process 10 times, with each adaptation executed on a training set of 90% of the total randomly chosen training set, whereas the remaining 10% served for validation purpose.

In the process of optimizing the sensor network installed in the user's home, with the aim of minimizing the number of sensors and installing them in optimal locations without losing measurement accuracy, the cost of the technology and user acceptance must be considered. Table 18 and Table 21 show the cost of the home sensor network for the different configurations for the two case studies considering a cost of 150 € for each Delta Dore DMB Tyxal+ PIR sensor and 100 € for each Delta Dore DO BL Tyxal+ door sensor, which are the sensors modeled in the simulation. To ensure greater acceptability by older people, it is thus recommended to reduce the number of sensors to be installed in the home. By optimizing the home sensor network configuration and relating costs to the effectiveness of the configuration, the behaviour of older people can be monitored with high accuracy while minimizing the installation costs. Considering, for example, the three configurations in Case Study 1, all of them provide high accuracy in measuring older users' ADLs, so it is appropriate to use the least expensive one that will still have a high impact on user monitoring while lowering costs. Optimizing the home sensor network consequently improves the process of remote monitoring of older people, enabling the deployment of cost-effective and prompt healthcare services, such as early detection of patient decline. This contributes to reduce the workload for hospitals, preventing frequent visits, and allowing the older person to age safely at home. Looking at the trend (orange line in Figure 49) of the ML accuracy and the number of sensors, by using a few sensors, the accuracy in classifying ADLs is still high (over 90%) while keeping costs low (blue line in Figure 49). Therefore, taking into account the minimization of the number of sensors and costs while guaranteeing high measurement accuracy, the optimal configuration of the home sensor network for Case Study 1 is the third that, with a total cost of 850 €, allows to achieve over 98% accuracy in ADLs classification using the DT algorithm, while for Case Study 2 it is the second that, with a cost of 300 €, allows to achieve 91% accuracy using the DT algorithm.

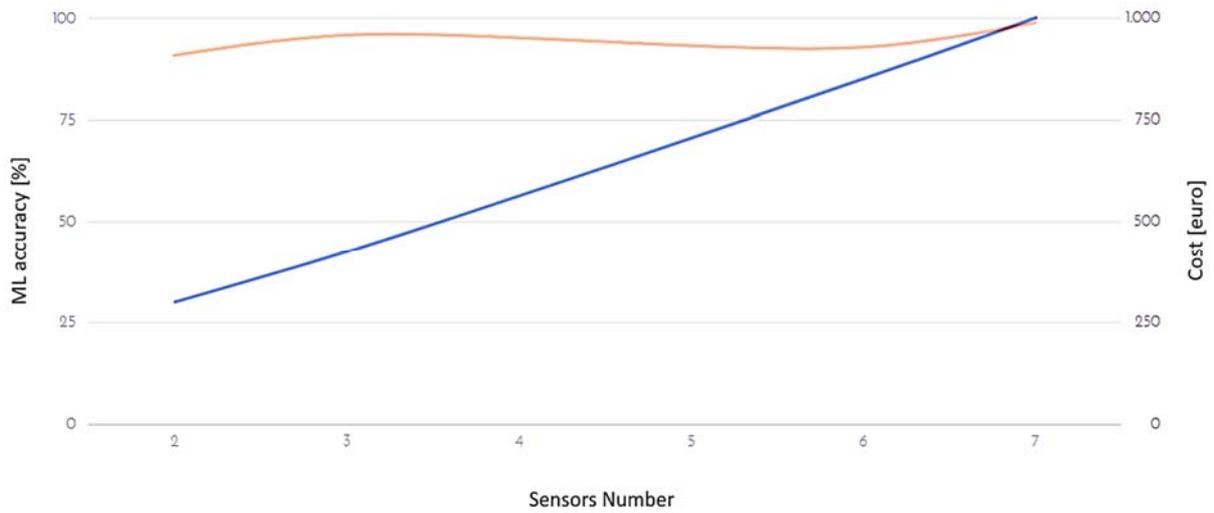


Figure 49. Cost-effectiveness of the home sensor network: ML accuracy in classifying ADLs in relation to the number of sensors (orange line), and cost of the home sensor network in relation to the number of sensors (blue line).

In conclusion, we proved that by analysing the accuracy of user’s ADLs classification using the DT algorithm, the home sensor network configuration can be modified to provide the most suitable design for the use case. The benefit of this method is that insufficient system designs can be detected at an early development stage and cost-benefit estimations for the sensors network can be done in advance, identifying the best compromise in terms of number of sensors, implementation cost and precision in the measurement of older people’s ADLs. The results of this study will then be used to determine the output of the Use Cases Configurator, i.e. the optimal configuration of the home sensor network to measure the activities of the older end-user based on the use case resulting from the inputs.

6. Conclusions

D4.6 identifies the sensing systems to measure user’s behaviours, emotions, and physiological parameters, investigating their flexibility, reliability and interoperability as criteria for the choice of sensors. The availability of the sensors has been also an important criterion that obliged to expand the list for the experiments in Japan.

The approach in this deliverable is based on the conclusions of deliverable D2.3 *Data Requirements of social and emotional computing* which set out the means to meet the possible requirements and needs for active and healthy ageing. Similarly, deliverables D3.4 *Storyboards of evidence-based scenarios* and D4.5, which is the first deliverable of the task of sensors identification carried out by the WP4, identified scenarios for the use of the e-VITA platform and determined the set of data needed to unfold these scenarios. User requirements and needs are thus defined by use cases which presuppose specific technologies. Each domain requires the integration of specific sensors to acquire heterogeneous data, and a coaching device to be selected based on user’s information, cultural and religious aspects, preferences, as well as the technical characteristics and functionalities performed. This task is performed by the Use Cases Configurator (UCC), a tool which aims at identifying the optimal configuration of the sensors network and coaching devices to be used based on user’s needs and requirements. Sensors meeting the use case requirements are partly already available in the e-VITA consortium, while others have been selected through in-dept market research. The specific mobile applications for the usage scenarios are instead available on the Android smartphone or tablet provided to the user as support device.

This document presents the sensors that meet the use cases defined by the WP3 (Table 22. Sensors associated with use cases). These sensors are grouped into three categories: user-related devices which are wearables, environmental devices which allows to maintain living comfort and well-being, and home-based devices that allows to infer the practices, activities and habits of the occupants. The paper presents the characteristics of the sensors, their performances, and how they are connected to the e-VITA platform.

<i>Use Cases Domain</i>	<i>Sensors</i>
<i>Daily Activities</i>	Delta Dore DMB TYXAL+, Delta Dore DO BL TYXAL+ EnOcean ETC-PIR, EnOcean ETB-OCS Netatmo Smart Indoor Air Quality Monitor EnOcean ET9-RHT Huawei Band 7 Oura Ring Smartphone/Tablet
<i>Health Coaching</i>	NEU XB-01 uSkin pillow

	Huawei Band 7 Oura Ring Smartphone/Tablet Delta Dore DMB TYXAL+, Delta Dore DO BL TYXAL+ EnOcean ETC-PIR, EnOcean ETB-OCS NETATMO Smart Indoor Air Quality Monitor EnOcean ET9-RHT
Social Connection	Smartphone/Tablet

Table 22. Sensors associated with use cases

Figure 50 shows an example of sensor network for the Cognitive training use case related to the Health coaching domain. The UCC, choosing from the sensing technologies identified in this document and considering the results of the sensor network optimisation, provides the appropriate set of sensors to acquire data and provide suitable services to achieve the user's goal. In this case, the devices selected from those identified are the NEU XB-01 (and its ABC App for cognitive training) and the supporting device (smartphone) required to run the ABC App.

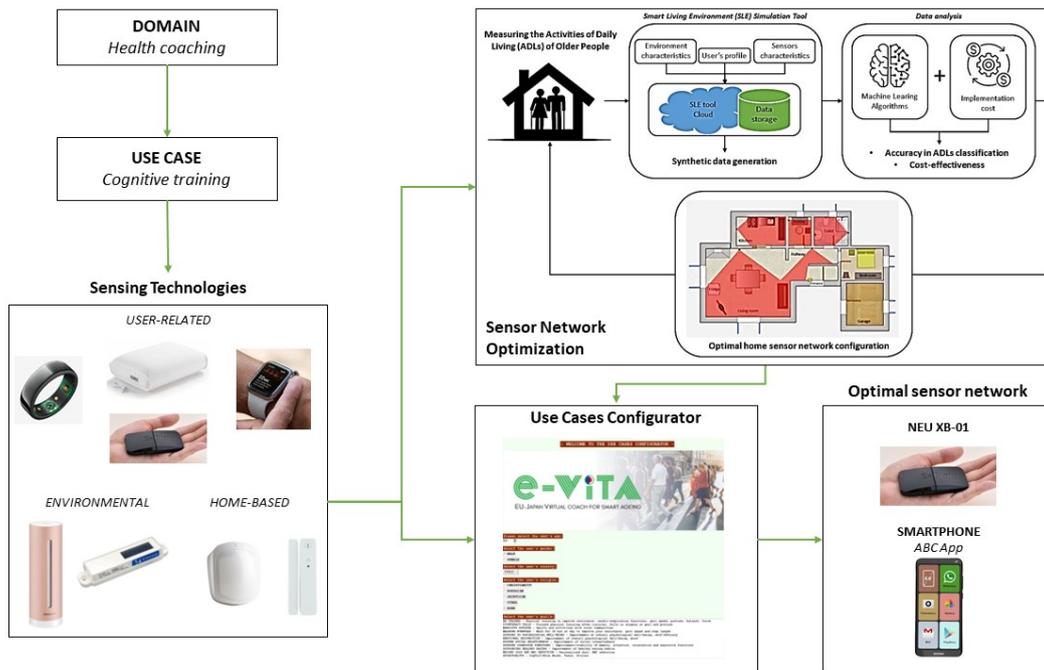


Figure 50. Example of sensor network identification for Cognitive training use case of the Health coaching domain

Figure 51 shows instead the optimal sensor network for the Environmental monitoring use case, which consists of IEQ monitoring to provide advice to the user to ensure his or her well-being. In this case, the device suitable for providing the service is the Netatmo Smart Air Quality monitor.

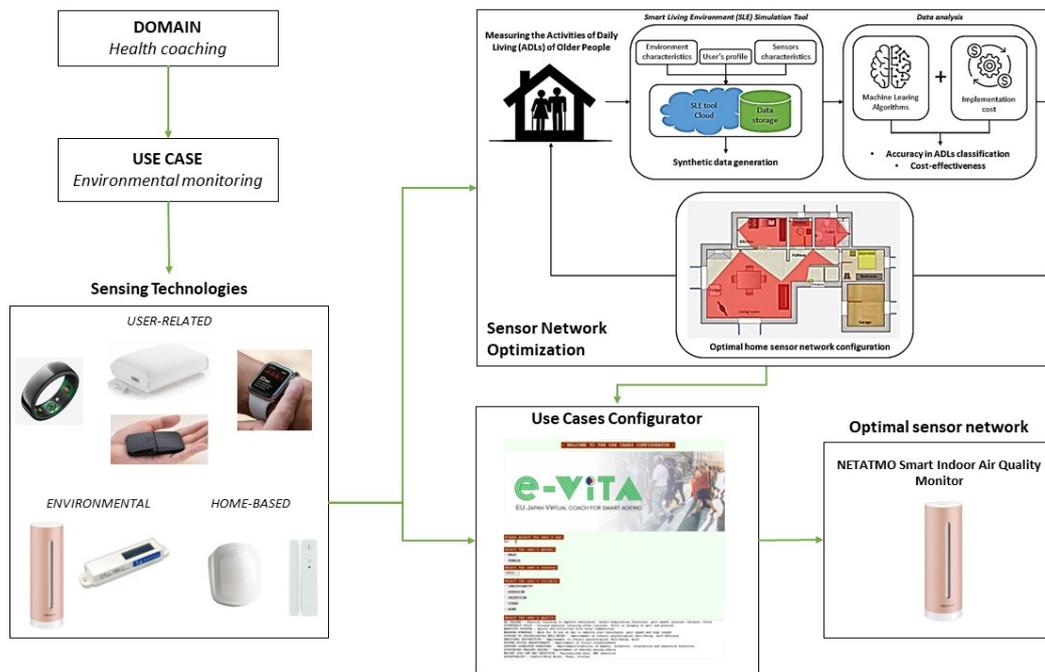


Figure 51. Example of sensor network identification for Environmental monitoring use case of the Health coaching domain

As just mentioned, environmental sensors can be used to measure indoor environmental quality, which has a determining effect on the health of the occupants, especially when it comes to older people. This paper presents the work that has been carried out by UNIVPM and AIST as a preliminary study to develop a methodology from a sensor network and based on IEQ monitoring to provide information and advice to older users. This approach could lead to greater user engagement with the virtual coach.

An important aspect for the integration of sensors of different nature is the consideration of interoperability which is presented in this deliverable. By invoking the e-VITA API, it is possible to store the data measured by the various sensors on a proprietary cloud, where they can be retrieved and analysed. Data collected are harmonized using standard data models to ensure interoperability in terms of data formats and semantics. Harmonized sensor data are sent to the FIWARE Context Broker that is in charge of managing the current measurements of the sensors and the contextualization. Data is also stored in an object storage to maintain historical records of the measurements. We therefore demonstrated that the FIWARE platform can be used to build a sensor network system that ensures interoperability.

This document also presented the work that have been carried out concerning the mobile application that allows to get high level information about the ADLs.

This deliverable finally deals with the optimization of the sensor network to obtain a good level of performance for the monitoring of daily activities while limiting the number of sensors that can be perceived as intrusive by the users. This work integrates the characteristics of home-based-device sensors. Using simulation tools, this work allows to establish optimization results also considering economic aspects in comparison with the gain in accuracy.

7. References

1. Fiware-Orion Available online: <https://fiware-orion.readthedocs.io/en/master/> (accessed on 9 December 2022).
2. ETSI - Welcome to the World of Standards! Available online: <https://www.etsi.org/> (accessed on 9 December 2022).
3. Google Assistant SDK Available online: <https://developers.google.com/assistant/sdk> (accessed on 9 December 2022).
4. Casaccia, S.; Jokinen, K.; Naccarelli, R.; Revel, G.M. Well-Being and Comfort of Ageing People Based on Indoor Environmental Conditions: Preliminary Study on Human-Coach Conversation. In Proceedings of the 2022 IEEE International Workshop on Metrology for Living Environment (MetroLivEn); May 2022; pp. 164–169.
5. Claudi, L.; Arnesano, M.; Chiariotti, P.; Battista, G.; Revel, G.M. A Soft-Sensing Approach for the Evaluation of the Acoustic Comfort Due to Building Envelope Protection against External Noise. *Measurement* **2019**, *146*, 675–688, doi:10.1016/j.measurement.2019.07.003.
6. Marques, G.; Pitarma, R. A Real-Time Noise Monitoring System Based on Internet of Things for Enhanced Acoustic Comfort and Occupational Health. *IEEE Access* **2020**, *8*, 139741–139755, doi:10.1109/ACCESS.2020.3012919.
7. Mujan, I.; Anđelković, A.S.; Munćan, V.; Kljajić, M.; Ružić, D. Influence of Indoor Environmental Quality on Human Health and Productivity - A Review. *Journal of Cleaner Production* **2019**, *217*, 646–657, doi:10.1016/j.jclepro.2019.01.307.
8. Vardaxis, N.G.; Bard, D.; Persson Waye, K. Review of Acoustic Comfort Evaluation in Dwellings—Part I: Associations of Acoustic Field Data to Subjective Responses from Building Surveys. *Building Acoustics* **2018**, *25*, 151–170, doi:10.1177/1351010X18762687.
9. Thomas, P.; Aletta, F.; Mynsbrugge, T.V.; Filipan, K.; Geetere, L.D.; Botteldooren, D.; Petrovic, M. Evaluation and Improvement of the Acoustic Comfort in Nursing Homes: A Case Study in Flanders, Belgium. 8.
10. Golmohammadi, R.; Darvishi, E.; Shafiee Motlagh, M.; Faradmal, J.; Aliabadi, M.; Rodrigues, M.A. Prediction of Occupational Exposure Limits for Noise-Induced Non-Auditory Effects. *Applied Ergonomics* **2022**, *99*, 103641, doi:10.1016/j.apergo.2021.103641.
11. EN 12665:2011 - Light and Lighting - Basic Terms and Criteria for Specifying Lighting Requirements Available online: <https://standards.iteh.ai/catalog/standards/cen/d7c62c9a-95ac-4ed8-9a40-862805aa5afc/en-12665-2011> (accessed on 3 February 2022).
12. Abdelhafiz, A.H.; Austin, C.A. Visual Factors Should Be Assessed in Older People Presenting with Falls or Hip Fracture. *Age and Ageing* **2003**, *32*, 26–30, doi:10.1093/ageing/32.1.26.
13. Guerry, E.; Gălățanu, C.D.; Canale, L.; Zissis, G. Luminance Contrast Assessment for Elderly Visual Comfort Using Imaging Measurements. *Procedia Manufacturing* **2019**, *32*, 474–479, doi:10.1016/j.promfg.2019.02.242.
14. Faculty of Architecture, Yasar University, Izmir, Turkey; Kunduraci, A.C. LIGHTING DESIGN FOR THE AGING EYES. *mijst* **2017**, *3*, 185–194, doi:10.20319/mijst.2017.33.185194.
15. Pigliatile, I.; Casaccia, S.; Morresi, N.; Arnesano, M.; Pisello, A.L.; Revel, G.M. Assessing Occupants' Personal Attributes in Relation to Human Perception of Environmental Comfort: Measurement Procedure and Data Analysis. *Building and Environment* **2020**, *177*, 106901, doi:10.1016/j.buildenv.2020.106901.
16. Morresi, N.; Casaccia, S.; Sorcinelli, M.; Arnesano, M.; Uriarte, A.; Torrens-Galdiz, J.I.; Revel, G.M. Sensing Physiological and Environmental Quantities to Measure Human Thermal Comfort

- Through Machine Learning Techniques. *IEEE Sensors Journal* **2021**, *21*, 12322–12337, doi:10.1109/JSEN.2021.3064707.
17. Yi, C.Y.; Peng, C.; Childs, C.; Robinson, D. Thermal Comfort Modelling of Older People Living in Care Homes: An Evaluation of Heat Balance, Adaptive Comfort, and Thermographic Methods. *Building and Environment* **2021**.
 18. Becker, R.; Paciuk, M. Thermal Comfort in Residential Buildings – Failure to Predict by Standard Model. *Building and Environment* **2009**, *44*, 948–960, doi:10.1016/j.buildenv.2008.06.011.
 19. Indraganti, M.; Rao, K.D. Effect of Age, Gender, Economic Group and Tenure on Thermal Comfort: A Field Study in Residential Buildings in Hot and Dry Climate with Seasonal Variations. *Energy and Buildings* **2010**, *42*, 273–281, doi:10.1016/j.enbuild.2009.09.003.
 20. Forcada, N.; Gangoles, M.; Casals, M.; Tejedor, B.; Macarulla, M.; Gaspar, K. Field Study on Thermal Comfort in Nursing Homes in Heated Environments. *Energy and Buildings* **2021**, *244*, 111032, doi:10.1016/j.enbuild.2021.111032.
 21. Casaccia, S.; Naccarelli, R.; Moccia, S.; Migliorelli, L.; Frontoni, E.; Revel, G.M. Development of a Measurement Setup to Detect the Level of Physical Activity and Social Distancing of Ageing People in a Social Garden during COVID-19 Pandemic. *Measurement* **2021**, *184*, 109946, doi:10.1016/j.measurement.2021.109946.
 22. Mendes, A.; Papoila, A.L.; Carreiro-Martins, P.; Bonassi, S.; Caires, I.; Palmeiro, T.; Aguiar, L.; Pereira, C.; Neves, P.; Mendes, D.; et al. The Impact of Indoor Air Quality and Contaminants on Respiratory Health of Older People Living in Long-Term Care Residences in Porto. *Age and Ageing* **2016**, *45*, 136–142, doi:10.1093/ageing/afv157.
 23. Simoni, M.; Jaakkola, M.S.; Carrozzi, L.; Baldacci, S.; Pede, F.D.; Viegi, G. Indoor Air Pollution and Respiratory Health in the Elderly. *European Respiratory Journal* **2003**, *21*, 15s–20s, doi:10.1183/09031936.03.00403603.
 24. Saenz, J.L.; Wong, R.; Ailshire, J.A. Indoor Air Pollution and Cognitive Function among Older Mexican Adults. *J Epidemiol Community Health* **2018**, *72*, 21–26, doi:10.1136/jech-2017-209704.
 25. Laurent, M.R.; Frans, J. Monitors to Improve Indoor Air Carbon Dioxide Concentrations in the Hospital: A Randomized Crossover Trial. *Science of The Total Environment* **2022**, *806*, 151349, doi:10.1016/j.scitotenv.2021.151349.
 26. Naccarelli, R.; Casaccia, S.; Pirozzi, M.; Revel, G.M. Using a Smart Living Environment Simulation Tool and Machine Learning to Optimize the Home Sensor Network Configuration for Measuring the Activities of Daily Living of Older People. *Buildings* **2022**, *12*, 2213, doi:10.3390/buildings12122213.
 27. Casaccia, S.; Romeo, L.; Calvaresi, A.; Morresi, N.; Monteriù, A.; Frontoni, E.; Scalise, L.; Revel, G.M. Measurement of Users' Well-Being Through Domotic Sensors and Machine Learning Algorithms. *IEEE Sensors Journal* **2020**, *20*, 8029–8038, doi:10.1109/JSEN.2020.2981209.
 28. Naccarelli, R.; Casaccia, S.; Revel, G. The Problem of Monitoring Activities of Older People in Multi-Resident Scenarios: An Innovative and Non-Invasive Measurement System Based on Wearables and PIR Sensors. *Sensors* **2022**, *22*, 3472, doi:10.3390/s22093472.
 29. Pietroni, F.; Casaccia, S.; Revel, G.M.; Scalise, L. Methodologies for Continuous Activity Classification of User through Wearable Devices: Feasibility and Preliminary Investigation. In Proceedings of the 2016 IEEE Sensors Applications Symposium (SAS); April 2016; pp. 1–6.
 30. Ooi, B.Y.; Beh, W.L.; Lee, W.; Shirmohammadi, S. Using the Cloud to Improve Sensor Availability and Reliability in Remote Monitoring. *IEEE Transactions on Instrumentation and Measurement* **2019**, *68*, 1522–1532, doi:10.1109/TIM.2018.2882218.
 31. Massaroni, C.; Nicolò, A.; Schena, E.; Sacchetti, M. Remote Respiratory Monitoring in the Time of COVID-19. *Front. Physiol.* **2020**, *11*, doi:10.3389/fphys.2020.00635.

32. Xing, Y.; Wang, T.; Zhou, F.; Hu, A.; Li, G.; Peng, L. EVAL Cane: Non-Intrusive Monitoring Platform with a Novel Gait-Based User Identification Scheme. *IEEE Transactions on Instrumentation and Measurement* **2020**, 1–1, doi:10.1109/TIM.2020.3009338.
33. Gochoo, M.; Tan, T.; Liu, S.; Jean, F.; Alhajjar, F.; Huang, S. Unobtrusive Activity Recognition of Elderly People Living Alone Using Anonymous Binary Sensors and DCNN. *IEEE Journal of Biomedical and Health Informatics* **2018**, 1–1, doi:10.1109/JBHI.2018.2833618.
34. Mora, N.; Grossi, F.; Russo, D.; Barsocchi, P.; Hu, R.; Brunswiler, T.; Michel, B.; Cocchi, F.; Montanari, E.; Nunziata, S.; et al. IoT-Based Home Monitoring: Supporting Practitioners' Assessment by Behavioral Analysis. *Sensors* **2019**, *19*, 3238, doi:10.3390/s19143238.
35. Piau, A.; Lepage, B.; Bernon, C.; Gleizes, M.-P.; Nourhashemi, F. Real-Time Detection of Behavioral Anomalies of Older People Using Artificial Intelligence (The 3-PEGASE Study): Protocol for a Real-Life Prospective Trial. *JMIR Research Protocols* **2019**, *8*, e14245, doi:10.2196/14245.
36. Shirali, M.; Bayo Montón, J.; Fernandez-Llatas, C.; Ghassemian, M.; Traver, V. Design and Evaluation of a Solo-Resident Smart Home Testbed for Mobility Pattern Monitoring and Behavioural Assessment. *Sensors* **2020**, *20*, 7167, doi:10.3390/s20247167.
37. Doyle, J.; Kealy, A.; Loane, J.; Walsh, L.; O'Mullane, B.; Flynn, C.; Macfarlane, A.; Bortz, B.; Knapp, R.B.; Bond, R. An Integrated Home-Based Self-Management System to Support the Wellbeing of Older Adults. *Journal of Ambient Intelligence and Smart Environments* **2014**, *6*, 359–383, doi:10.3233/AIS-140270.
38. Eisa, S.; Moreira, A. A Behaviour Monitoring System (BMS) for Ambient Assisted Living. *Sensors* **2017**, *17*, 1946, doi:10.3390/s17091946.
39. Alshammari, N.; Alshammari, T.; Sedky, M.; Champion, J.; Bauer, C. OpenSHS: Open Smart Home Simulator. *Sensors* **2017**, *17*, 1003, doi:10.3390/s17051003.
40. Synnott, J.; Nugent, C.; Jeffers, P. Simulation of Smart Home Activity Datasets. *Sensors* **2015**, *15*, 14162–14179, doi:10.3390/s150614162.
41. Renoux, J.; Klugl, F. SIMULATING DAILY ACTIVITIES IN A SMART HOME FOR DATA GENERATION. In Proceedings of the 2018 Winter Simulation Conference (WSC); December 2018; pp. 798–809.
42. Buchmayr, M.; Kurschl, W.; Küng, J. A Simulator for Generating and Visualizing Sensor Data for Ambient Intelligence Environments. *Procedia Computer Science* **2011**, *5*, 90–97, doi:10.1016/j.procs.2011.07.014.
43. Helal, S.; Lee, J.W.; Hossain, S.; Kim, E.; Hagrass, H.; Cook, D. Persim - Simulator for Human Activities in Pervasive Spaces. In Proceedings of the 2011 Seventh International Conference on Intelligent Environments; July 2011; pp. 192–199.
44. Kormányos, B.; Pataki, B. Multilevel Simulation of Daily Activities: Why and How? In Proceedings of the 2013 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA); July 2013; pp. 1–6.
45. Bouchard, K.; Ajroud, A.; Bouchard, B.; Bouzouane, A. SIMACT: A 3D Open Source Smart Home Simulator for Activity Recognition with Open Database and Visual Editor. *International Journal of Hybrid Information Technology (IJHIT)*, **2012**, *Volume 5*, 13–32.
46. Park, J.; Moon, M.; Hwang, S.; Yeom, K. CASS: A Context-Aware Simulation System for Smart Home. In Proceedings of the 5th ACIS International Conference on Software Engineering Research, Management & Applications (SERA 2007); August 2007; pp. 461–467.
47. Caruso, M.; Ilban, Ç.; Leotta, F.; Mecella, M.; Vassos, S. Synthesizing Daily Life Logs through Gaming and Simulation. In Proceedings of the Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication; Association for Computing Machinery: New York, NY, USA, September 8 2013; pp. 451–460.

48. Buchmayr, M.; Kurschl, W.; Küng, J. A Simulator for Generating and Visualizing Sensor Data for Ambient Intelligence Environments. *Procedia Computer Science* **2011**, *5*, 90–97, doi:10.1016/j.procs.2011.07.014.
49. Synnott, J.; Chen, L.; Nugent, C.D.; Moore, G. The Creation of Simulated Activity Datasets Using a Graphical Intelligent Environment Simulation Tool. In Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society; August 2014; pp. 4143–4146.
50. Ariani, A.; Redmond, S.J.; Chang, D.; Lovell, N.H. Simulation of a Smart Home Environment. In Proceedings of the 2013 3rd International Conference on Instrumentation, Communications, Information Technology and Biomedical Engineering (ICICI-BME); November 2013; pp. 27–32.
51. Nishikawa, H.; Yamamoto, S.; Tamai, M.; Nishigaki, K.; Kitani, T.; Shibata, N.; Yasumoto, K.; Ito, M. UbiREAL: Realistic Smartspace Simulator for Systematic Testing. In Proceedings of the UbiComp 2006: Ubiquitous Computing; Dourish, P., Friday, A., Eds.; Springer: Berlin, Heidelberg, 2006; pp. 459–476.
52. Casaccia, S.; Rosati, R.; Scalise, L.; Revel, G.M. Measurement of Activities of Daily Living: A Simulation Tool for the Optimisation of a Passive Infrared Sensor Network in a Smart Home Environment. In Proceedings of the 2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC); May 2020; pp. 1–6.
53. Pirozzi, M. Development of a Simulation Tool for Measurements and Analysis of Simulated and Real Data to Identify ADLs and Behavioral Trends through Statistics Techniques and ML Algorithms. Ph.D. Thesis, Univeristà Politecnica delle Marche, 2020.
54. Atallah, L.; Lo, B.; Ali, R.; King, R.; Yang, G.-Z. Real-Time Activity Classification Using Ambient and Wearable Sensors. *IEEE Transactions on Information Technology in Biomedicine* **2009**, *13*, 1031–1039, doi:10.1109/TITB.2009.2028575.
55. Ariani, A.; Redmond, S.J.; Chang, D.; Lovell, N.H. Software Simulation of Unobtrusive Falls Detection at Night-Time Using Passive Infrared and Pressure Mat Sensors. In Proceedings of the 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology; August 2010; pp. 2115–2118.
56. Hu, Y.-J.; Yu, M.-C.; Wang, H.-A.; Ting, Z.-Y. A Similarity-Based Learning Algorithm Using Distance Transformation. *IEEE Transactions on Knowledge and Data Engineering* **2015**, *27*, 1452–1464, doi:10.1109/TKDE.2015.2391109.
57. Francillette, Y.; Bouchard, B.; Bouchard, K.; Gaboury, S. Modeling, Learning, and Simulating Human Activities of Daily Living with Behavior Trees. *Knowl Inf Syst* **2020**, doi:10.1007/s10115-020-01476-x.
58. Roy, P.C.; Bouchard, B.; Bouzouane, A.; Giroux, S. Ambient Activity Recognition in Smart Environments for Cognitive Assistance Available online: www.igi-global.com/article/ambient-activity-recognition-in-smart-environments-for-cognitive-assistance/95226 (accessed on 1 October 2020).
59. Mohanapriya, M.; Lekha, J. Comparative Study between Decision Tree and Knn of Data Mining Classification Technique. *J. Phys.: Conf. Ser.* **2018**, *1142*, 012011, doi:10.1088/1742-6596/1142/1/012011.
60. Rahmadani, S.; Dongoran, A.; Zarlis, M.; Zakarias Comparison of Naive Bayes and Decision Tree on Feature Selection Using Genetic Algorithm for Classification Problem. *J. Phys.: Conf. Ser.* **2018**, *978*, 012087, doi:10.1088/1742-6596/978/1/012087.