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ACTIVA. Innovation in Quality of Care for Nursing Homes through Activity Recognition

ALICIA MONTORO[1], JOSÉ L. LÓPEZ[1],CHRIS NUGENT[2], (Member, IEEE) and MACARENA ESPINILLA[1]

[1]Department of Computer Science, University of Jaén, 23071, Jaén, Spain (email: amlendin@ujaen.es; llopez@ujaen.es; mestevez@ujaen.es)
[2]Ulster University, School of Computing, Belfast, UK.(e-mail: cd.nugent@ulster.ac.uk)

Corresponding author: Alicia Montoro (e-mail: amlendin@ujaen.es).

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ABSTRACT There are an increasing number of elderly people with various pathologies and care needs, making nursing homes one of the most suitable places for them to live. The demand for nursing homes is expected to increase further in the coming years due to the growing life expectancy. Human activity recognition (HAR) approaches are an excellent resource that can be deployed in nursing homes to detect an inhabitant's activity through sensors in the environment. Despite the many theoretical approaches to HAR proposed in the literature, there is a significant lack of implementation in real environments. In this paper, we present an activity recognition approach deployed to monitor a floor of a nursing home using a mobile app called ACTIVA, which allows caregivers to track inhabitants and be notified of anomalies in real-time. The ACTIVA system relies on successful tools proposed for HAR, such as the use of fuzzy logic techniques, linguistic protoforms, and temporal windows to infer the location and activity of each inhabitant in a multi-occupancy environment. These tools have proven effective in inferring inhabitant activity and location, allowing for more precise and detailed monitoring. ACTIVA provides multiple benefits in terms of providing more information on the activities performed by residents, reducing stress for caregivers, and increasing safety for the residents being monitored. To evaluate the impact of ACTIVA app, we gathered feedback from different stakeholders and found overall positive satisfaction levels. Our approach represents a significant step towards the practical implementation of HAR approaches in real nursing home environments.

INDEX TERMS Activity recognition, anomaly notification, fuzzy logic, linguistic protoforms, monitoring of elderly people, nursing homes.

I. INTRODUCTION

Population ageing is a real and tangible challenge today. The World Health Organisation (WHO) predicts that by 2030, 1 in 6 people in the world will be 60 years of age or older. Moreover, by 2050 the world's population aged 60 and above will double to approximately 2.1 billion [1]. Related to ageing, although not always because of it, different conditions appear that harm the elderly, diminishing their physical, cognitive or social capacities and requiring professional care and treatment [2], [3]. Among these social afflictions, there is also the unwanted loneliness suffered by elderly people which can greatly affect their quality of life [4], [5].

Care homes for the elderly can provide suitable care and attention 24 hours a day, seven days a week, as they offer personalised professional care and support [6]. However, caregivers in nursing homes often suffer from work-related stress due to the continuous daily workload. This stress not only affects the caregivers, but also indirectly affects the elderly people being cared for [7], [8].

Human activity recognition (HAR) approaches [9]–[11] are an excellent tool to monitor the activities performed by a person within an environment from data generated by ubiquitous sensor devices without human intervention. However, despite the excellent theoretical results achieved in the literature, there is a significant gap between proposed HAR approaches involving systems adapted to specific real environments to monitor multiple elderly people and the evaluation of such systems by both caregivers and residents, as well as other stakeholders (family members or nursing home directors).

In order to fill this gap in our society, this work proposes a HAR system that monitors multiple elderly residents in a nursing home environment: the ACTIVA system [12]. For this purpose, a cloud and fog architecture was used, which has given excellent results in activity recognition [13], where the location of the inhabitant is first deduced and then the activity is identified. Given the challenge of multi-occupancy in human activity recognition, as is the case of a nursing home, BLE beacons and BLE wearable devices have been used to locate inhabitants within the environment and detect who is carrying out the activity [14]–[16] using fuzzy logic.

To do so, the use of fuzzy logic is used for activity recognition with sensors as it allows for the handling of uncertainty and imprecision inherent in sensor data [10], [13], [15], [17]. In these types of systems, sensors may provide inaccurate or noisy data, making it challenging to identify the activities performed by users accurately. Fuzzy logic enables dealing with this uncertainty by representing and manipulating incomplete or inaccurate data through fuzzy sets and logic operations. Furthermore, fuzzy logic can model the ambiguity of natural language, which is useful in the context of human activity recognition, where precise definitions can be challenging to establish. The use of linguistic protoforms in fuzzy logic-based activity recognition enables more natural expressions of the descriptions of the activities performed by users, improving the accuracy and interpretation of the information obtained [13], [18]–[20].

Motion, vibration, and interruption sensors have been deployed in the environment to obtain sensor data [14], [21]–[24]. These types of sensors have been widely used for activity recognition in smart environments, as evidenced by previous research . The sensor data is segmented into temporal windows, and fuzzy linguistic protoforms are used to evaluate activity, which has also been a popular approach in recent studies.

The proposed system not only recognises the activities of the elderly residents of the care home, but also integrates a mobile application called ACTIVA designed for caregivers. In this way, the caregivers are informed in real time about the activities and the location of the inhabitants on the floor of the nursing home, allowing ubiquitous monitoring of all the inhabitants, which leads to a decrease in the caregivers' work-related stress.

Therefore, the main innovation of the ACTIVA system is recognising activities required by caregivers on a floor of a nursing home so that inhabitants are monitored in real time with two objectives: i) to increase the safety of the elderly residents, so that in case of any anomaly the caregivers are immediately informed through the ACTIVA app, and ii) to reduce stress on the caregivers as they can track the inhabitants in real time and receive notifications about anomalies. In addition, another novelty of our proposal is our device-free [25] sensor data collection method. This facilitates the implementation of these HAR systems in real environments, as the person to be monitored does not need to interact with the devices (in the environment or on him/herself) in order for the system to provide a response. For this purpose, the sensors are distributed in the monitoring area trying to minimise the modification of the environment in such a way that the inhabitant is as unaware as possible of the system.

Finally, in this paper we present a full evaluation of the impact of the ACTIVA system and the ACTIVA app with the input of different stakeholders – 23 participants for each profile (caregivers, the elderly residents in the nursing home, family members of the residents, the director of the nursing home, and social and health care professionals).

The paper is structured as follows. Firstly, a review of current works related to the recognition of human activities is presented. Then, the ACTIVA human activity recognition system deployed on one floor of a nursing home will be presented. The application domain, as well as the acquisition and communication of sensor data, will be described. Furthermore, the fog nodes implemented in each room, the cloud platform and, finally, the application for caregivers to monitor activities will be presented. Then, the results of the comprehensive impact evaluation of the ACTIVA system will be presented, taking into account the different stakeholders' points of view. Finally, the conclusions drawn from this work are presented and future work is outlined.

II. RELATED WORKS

This section reviews existing work on intelligent systems for the recognition of human activities in daily life.

Human activity recognition (HAR) is still an ongoing challenge for the scientific community. The literature contains multiple works related to this type of recognition: [25]–[27]. Firstly, HAR systems are usually differentiated according to the way in which the data is acquired: object-tagged [28], wearables [29], device-free [25], [30], [31] or hybrids.

In systems that use an object-tagged [28] approach, sensors are usually attached to objects associated with the activities to be recognised; for example, installing an opening sensor on the front door to know when the person leaves the house. In wearable-based [29] approaches, the system collects data directly from sensors embedded in elements worn by the inhabitant, such as a T-shirt or an activity wristband. In both cases, the user must interact directly with the elements that have the sensor attached. This type of data collection can be problematic if the monitored users are unwilling to use new technologies and often the sensorised elements tend to be very uncomfortable to use.

Three main categories of human activity detection are identified in the literature [25]: action-based, interaction-based and motion-based. The first group refers to the recognition of gestures, postures, behaviour, activities of daily living, falls and ambient assisted living. In the second group, the user interacts with objects within the environment. Finally, the third group includes tracking, motion detection and people counting.

The systems used for human activity recognition are based on activity classification. This classification is usually carried out by supervised algorithms that have been trained to recognise patterns between the features and the labelling of activities in a dataset. A multitude of proposed models can be found in the literature [27], [32]–[35], ranging from machine learning models that make use of classifiers based on decision trees, k-nearest neighbours, support vector machines, among others, and even deep learning [27], [36]. In addition, other elements such as indoor location systems [15] are included to support activity recognition and thus solve the problem of multi-occupancy.

One of the main problems not addressed by activity recognition models in the literature is the recognition in a multi-occupancy environment [37] that our ACTIVA system is capable of.

The great majority of these HAR systems present an activity classification model and are validated through experimentation. But they do not use the knowledge gained to provide user monitoring. For instance, in a nursing home environment, simultaneous monitoring of all inhabitants is essential. This allows for a faster and more effective response by the social and health care staff. In the case of intelligent environments, software solutions exist to manipulate and monitor all the devices in a system. An example of this type of visualisation is the case of the UJAmI SmartLab [38].

Nowadays, there is a strong need for environments which allow elderly people to gain independence without the need for them to interact with any kind of technology [39]. HAR systems play a key role in this area. These need, on the one hand, to detect human activities and, on the other hand, to provide feedback to caregivers. Therefore, it is necessary to ensure adequate methods for real-time and simultaneous monitoring of people.

In the literature, there are a number of works that explore this approach [40], [41]. Designing a wearable gadget that can measure vital signs, detect falls and automatically alert care providers in the event of an emergency is the goal of the CAALYX health care project [42], which is financed by the European Union (EU). Its ability to report the patient's current medical condition and location is crucial since it enables the emergency team to respond promptly.

Preetham Ganesh et al. [43] define a system that is able to distinguish different physical activities. In addition, they provide a mobile application that can generate a report of the activities performed and whether the movements of each have been executed correctly.

Moreover, Luigi Bibbo et al. [44] present a system capable of monitoring an inhabitant in an enclosed space, and distinguish six types of activities: walking, running, sitting, standing, upstairs and downstairs. For this system, they implemented a mobile application that displays the activity detected for a single inhabitant.

Finally, there are also works which provide software with the aim of improving experimentation. This is the case of Susanna Spinsante et al. [45] whose application facilitates the acquisition and labelling of data for each kind of activity. Similarly, the work of Igor Natal et al. [46] allows the outdoor activity being carried out to be specified.

Another important aspect in each proposed system is performing some type of quantitative evaluation. In general, this assessment is usually performed using accuracy as the main characteristic, although other parameters such as F1 score, recall, precision and ROC curve are also measured [9]–[11], [15], [19], [20], [23], [30]–[32], [47]. Thus, it is possible to compare different methods based on these metrics.

We are also seeing increased evaluations based on the parameters of the Sustainable Development Goals (SDGs) [48]. This type of assessment focuses on each of the 17 goals through 232 indicators [49].

In our case, we bring a novelty with respect to traditional evaluations: an impact assessment of the ACTIVA system with input from different stakeholders.

This paper proposes a human activity detection system focused on the operational context of ageing. This system provides a mobile application for real-time monitoring of a set of users simultaneously using a mainly device-free data acquisition methodology.

III. ACTIVA SYSTEM

The ACTIVA system allows the recognition of multi-occupancy activities in real time. It was deployed on a nursing home floor with the aim of i) increasing the safety of the elderly residents through monitoring and immediate detection of anomalies and ii) reducing the caregivers' stress by having a mobile app to track the residents' activities and report any anomaly.

The proposed system follows a fog-cloud architecture with two layers: the fog layer and the cloud layer. The fog layer is composed of several fog nodes located in each room, which collect the data generated by the sensors in each of the shared rooms. The cloud layer is composed of a cloud platform that collects all the information generated in each fog node to identify, on the one hand, each inhabitant's location and, on the other hand, the activity they are performing in a multi-occupancy environment. The ACTIVA app for nursing home caregivers connects to the platform to monitor the residents ubiquitously and in real time, receiving alerts through notifications.

It is important to note that the ACTIVA system and its app uses binary data and integer values, and at never stores private user data unlike other sensors such as cameras or other systems [50], [51], and to identify each user is done numerically and anonymously.

The general approach used for the ACTIVA system in the nursing home is presented in Figure 1 and will be described below. For this purpose, first the nursing home where the ACTIVA system is deployed is described; next, the data acquisition and communication method is presented; then the fog node processing and the cloud platform are described; and finally the mobile application for the caregivers is presented.

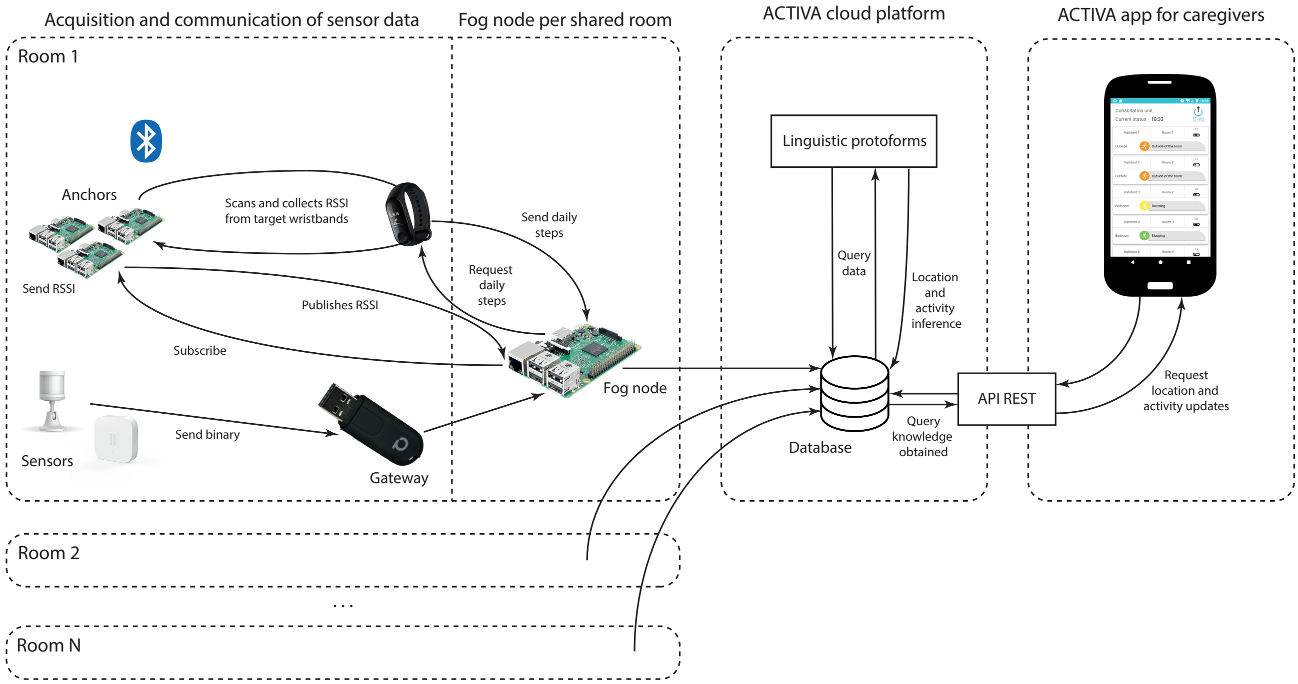

FIGURE 1. ACTIVA system architecture based on a fog-cloud architecture.

A. APPLICATION DOMAIN DESCRIPTION

The ACTIVA intelligent system has been proposed for the recognition of human activities in a floor of a nursing home in Jaén (Spain). Residents live together on the same floor and in rooms shared by two people. Each room has a shared bathroom and a bedroom with individual furniture for each inhabitant: a bedside table, a bed, a chair, a wardrobe and other elements such as shelves. Each of the rooms is approximately 6.67 metres wide and 3.04 metres high, with a floor area of 20.28 m^2. In addition, they have common areas shared by all residents: the central corridor, an area for eating and leisure activities and, finally, a place for relaxation and multimedia entertainment on the same floor.

In this context, the activities to be monitored and the locations detected have been defined according to the information provided by the nursing home caregivers and director. Specifically, the activities of showering, using the toilet, dressing, sleeping and leaving the room were defined. In addition, a series of locations to be detected between the different living areas within the floor were defined. The location of the inhabitants is of vital importance to be able to discern which resident is carrying out an activity due to the fact that they are shared rooms and it is usual for more than one person to be inside the rooms. In this case, the locations required by the caregivers were the bathroom, the bedroom and outside the room. Table 1 summarises the locations and activities to be recognised by the ACTIVA system.

TABLE 1. Summary of relevant locations and detected daily activities.

Relevant locations	Bedroom
	Bathroom
	Outside the room
Daily activities	Sleeping
	Dressing
	Showering
	Using the toilet
	Exiting the room

B. SENSOR DATA ACQUISITION AND COMMUNICATION

One of the biggest challenges in the recognition of human activities within the nursing home was the multi-occupancy factor.Not only did we have to account for the people living in the rooms, but also different staff that can access the rooms, such as cleaning staff, nurses, caregivers, medical staff, etc. Therefore, in this work we propose an approach that determines, firstly, the location of the person within the space and, secondly, the activity they are performing within the space through the sensors located in the room.

For location and activity detection, it is essential to deploy a series of devices and sensors that collect sensor data generated in the environment. Although there are various sensing methods in the literature, a device-free [25] data acquisition method is proposed in the ACTIVA system. The advantages of this type of monitoring is that it allows the system to respond without the need for the user to interact with the devices directly, and the system is completely transparent to

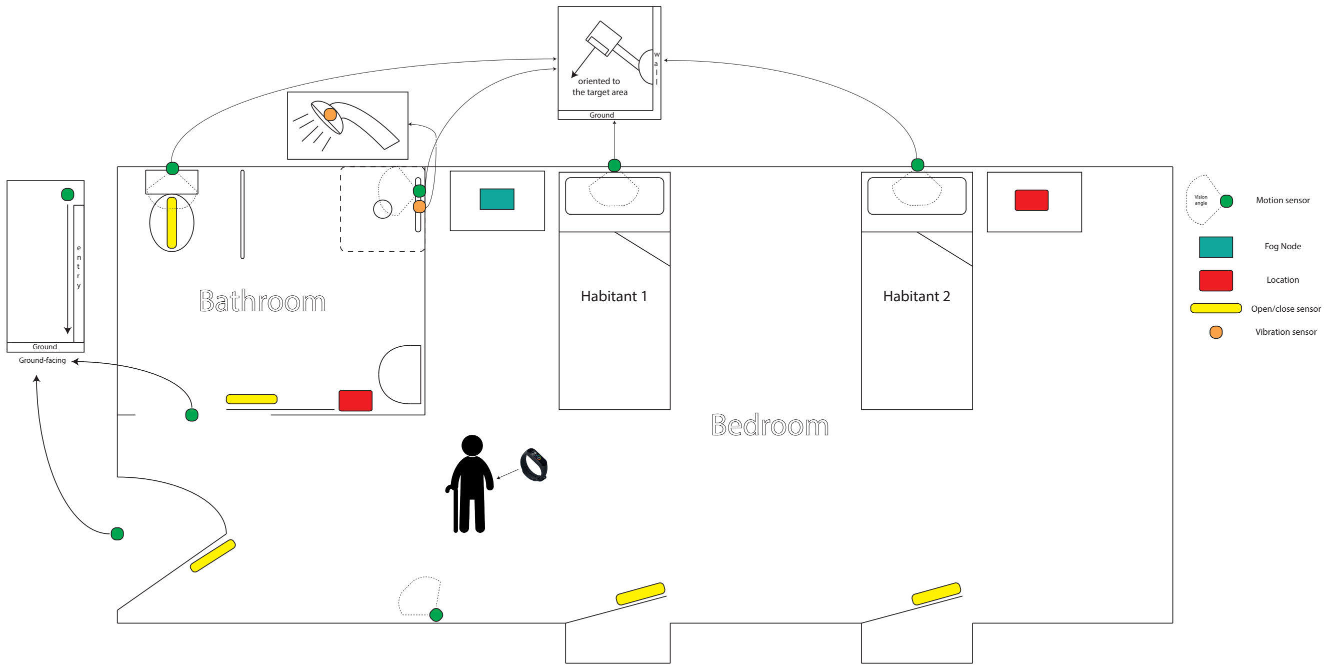

FIGURE 2. Room plan of the nursing home with each of the sensors and devices deployed.

the elderly resident.

Figure 2 shows the set of sensors deployed in one of the rooms of the nursing home for indoor location detection and activity recognition within the nursing home.

These sensors are used, on the one hand, for location detection (BLE beacons and BLE wearable wristband) and, on the other hand, for activity detection (vibration, motion and interruption sensors). The following sections describe the acquisition of data from these sensors and their communication with the fog node in each room.

1) RSSI for indoor location

Inhabitant location in the ACTIVA system is based on Received Signal Strength Indicator (RSSI) values, an intrinsic characteristic of wireless communications [15]. In our proposal, Bluetooth Low Energy (BLE) wireless technology has been chosen due to its low cost, low power consumption and the large number of devices that support this type of connection.

RSSI is a unit of power expressed in decibels relative to a milliwatt (dBm or $dBmW$). This value provides information on the signal strength between devices, in this case BLE connection. These strength values are negative values in the range of $[0, -100dBm]$. The lower the signal strength, the higher the negative value, i.e. zero would imply that the device is as close as possible to the BLE connection. In addition, the location of many obstacles can influence the strength of this RSSI signal. This uncertainty associated with the technology requires the use of pre-processing techniques such as time windows and the application of fuzzy logic models [15].

For wireless location detection, two types of elements are defined: the anchor and the BLE beacon [15]. The function of the anchor is to scan the RSSI of the beacon with a certain frequency whenever it is in range. In the ACTIVA system, an activity wristband with BLE 4.2 has been selected as the beacon and a small single-board computer has been selected as the anchor. This enables processing while altering the environment as little as possible. Specifically, the following devices have been used for location detection.

- Raspberry Pi (anchor) [1]. It scans the BLE beacons and sends the RSSI to the fog node every second via the Message Queuing Telemetry Transport (MQTT) protocol.
- Activity wristband (beacon)[2]. Device with BLE connection used to locate the inhabitant via RSSI.

As mentioned above, the ACTIVA system is device-free [25]. Thus, the elderly resident does not have to interact with the activity wristband at any time, just wear it. Therefore, the battery level will also be monitored so that the caregivers are the ones who have this information and know when to charge the devices. It should be noted that the chosen wristband has a battery life of approximately 20 days without interacting with it, just by wearing it, as is the case with the ACTIVA system.

Raspberry Pi is deployed in the relevant monitoring locations. In this case, the locations requested by the caregivers are within the residents' rooms: bedroom, bathroom and outside. These locations are critical because they are areas where the inhabitant is independent and where unwanted situations are more likely to occur. Three anchor devices are deployed

[1]https://www.raspberrypi.com/products/raspberry-pi-4-model-b/
[2]https://www.amazon.es/xiaomi-band-3/s?k=xiaomi+mi+band+3

in each room: one for the bathroom near the sink and two for the bedroom, one on each bedside table.

2) Environmental data for HAR

Given the activities requested by the nursing home (showering, using the toilet, dressing, sleeping and leaving the room), we proposed using motion sensors, interruption sensors to detect the opening and closing of drawers and doors, and vibration sensors which use the ZigBee protocol.

The selected devices for the ACTIVA system and their function within the shared room are described below.

- Vibration sensor [3]. It detects vibration in items, devices, etc. and sends signals to actuators or other systems in the environment. This sensor is attached to the shower head and its purpose is to detect whether the inhabitant is taking a shower.
- Motion and light sensor [4]. It detects motion and lighting. It sends signals to other devices and actuators. In this case, this type of sensor has several purposes depending on its placement:
    1) Shower: sensor attached to the wall facing the shower area. Used as a complement to the movement sensor to detect showering.
    2) Toilet: sensor attached to the wall facing the toilet area. Used to detect whether the inhabitant is using the toilet.
    3) Beds: sensor attached to the wall facing a single bed. Two sensors deployed for this purpose, one for each bed. Their purpose is to detect whether the inhabitant is in bed and sleeping.
    4) Doors: attached to the door lintel, horizontally oriented. Monitors movement between the location zones.
- Opening and closing sensor [5]. Access control to rooms, opening and closing of appliances, furniture, others. Like the motion sensor, it has several purposes:
    1) Doors: attached to bathroom and bedroom access doors. Used as an addition to the relevant locations, confirming an interaction by the inhabitant moving from one area to another.
    2) Wardrobes: attached to the wardrobe doors. Used to detect whether the user is getting dressed.
    3) Toilet: sensor attached to the lid. Used to detect if the inhabitant is using the toilet and serves as a complement to the movement sensor.

C. FOG NODE PER SHARED ROOM

The fog core is in charge of collecting all the data within a shared room that comes from the sensors and devices located in the room.

The data is sent locally over the MQTT communication protocol, using a publisher-subscriber methodology [24]. This element performs multiple functions: broker service for the MQTT protocol, data reception and processing, and sending and persistence of data.

The MQTT protocol is essential to send and receive data because the system is composed of multiple devices that collect data individually and there is no physical connection between them. To this end, it is necessary to maintain a server that accepts messages posted by clients and broadcasts them to the clients. This element is usually called a broker and, in this case, it is located in the fog node. There is a wide variety of brokers. Our system uses the Eclipse Mosquitto [52] broker as it is open source.

In our proposal, the fog node is in charge of subscribing to each of the sensors or devices in the system and receiving the changes that occur over time. Some of these data, such as RSSI values received from the anchor elements, are processed. For this type of data, aggregation functions are applied in a space of time, i.e. temporal windows that are usually defined by a window size s (time covered by the window usually in seconds) and a set of samples as a function of a time t. Following the methodology presented in [13] a temporal window of 10 seconds with the maximum aggregation operator is proposed.

Some of the commercial sensors –opening and closing, movement and light detection, and vibration sensors– are based on the ZigBee protocol [53], so an intermediate element is needed to allow them to communicate with the rest of the system elements. For this purpose, the ConBee II[6] device has been used, together with the open source Home Assistant [54] software.

ConBee II is a device that allows a single-board computer (SBC) to be converted into a universal Zigbee gateway, enabling remote connection to commercial sensors through it. It has an operating range of up to 30 meters in enclosed spaces. Devices that are further are connected through the Zigbee Mesh network. All mains-powered Zigbee devices, such lights and plugs, function as repeaters and may route the signal in this network. In addition, it has Home Assistant integration.

Home Assistant allows the integration of multiple smart devices in order to monitor and automate certain aspects within a smart home. In this case, its function is to communicate with ConBee II to receive data from the commercial sensors. It is also responsible for publishing the data received through MQTT communication, allowing the data to be received without the need to connect directly via the ZigBe protocol.

These processes, along with the anchor elements, are encapsulated in a Raspberry Pi 4B "4B" 4GB. This type of device is an SBC, which is characterised by having all the components of a computer on a single board. SBCs are compact – in this case, a size of *85* x *56* mm. This affects the environment as little as possible and has low consumption at *500* mA. Although this model has BLE connection, it has

[3] https://www.aqara.com/eu/vibration_sensor.html
[4] https://www.aqara.com/eu/motion_sensor.html
[5] https://www.aqara.com/eu/door_and_window_sensor.html
[6] https://phoscon.de/en/conbee2

RSSI COLLECTION

RSSI	
id	Random value given by MongoDB
timestamp	Time in Unix units. eg: 1669710741.65111
rssi	Represents the strength of this RSSI signal. eg:-74
id_anchor	Represents the Raspberry Pi which collects the RSSI data. eg: 7
id_beacon	Represents the habitant. eg: 4

INFERENCE COLLECTION

LOCATION	
id	Random value given by MongoDB
timestamp	Time in Unix units. eg: 1669710741.65111
location	Represents the different rooms. eg. Bathroom

ACTIVITY	
id	Random value given by MongoDB
timestamp	Time in Unix units. eg: 1669710741.65111
activity	Represents the different activities. eg. Sleep

ALL SENSORS AND WRISTBAND COLLECTION

SENSOR	
id	Random value given by MongoDB
timestamp	Time in Unix units. eg: 1669710741.65111
state	ON or OFF
id_sensor	Represents the associated number sensor. eg: 7

WRISTBAND	
id	Random value given by MongoDB
timestamp	Time in Unix units. eg: 1669710741.65111
steps	Steps number. eg: 155
battery	Baterry percentage. eg: 67
id_beacon	Represents the habitant. eg: 4

FIGURE 3. Database collections from ACTIVA system.

been fitted with a nano[7] USB adapter with BLE version 4.2. To reduce the use of SBCs, the fog node has been reused for one of the anchors.

Finally, once the data has been collected and processed correctly in the fog node, it is sent to a database in the cloud for persistent storage. This database can be consulted through the ACTIVA platform. The database has three collections (see Fig. 3), one for the RSSI signal, one for the location inference and one with the data from the sensors and the wristband. In addition, there is another collection that has not been shown because it is not relevant, but it is where the data from the sensors are associated with each room.

D. ACTIVA SYSTEM CLOUD PLATFORM

In the cloud platform, a crowdsourcing [55], [56] architecture has been chosen, due to the fact that an intelligent core is used outside the local system in charge of the logic for obtaining knowledge. This intelligent core performs the inference of the real-time location and daily activities of each and every monitored resident of the nursing home. For this purpose, the core performs detection based on fuzzy logic and linguistic protoforms [13] with the input of expert knowledge. In addition, it has rules for the notification of certain events such as low battery of the different devices in the system and the activity wristband.

In this proposal, the platform's detection of daily activities is supported by a classification model based on fuzzy logic for the detection of inhabitants' locations. This model, created by A.P. Albín et al. [15], is based on a two-level fuzzy methodology: by proximity and by temporality.

In the first level, a trapezoidal membership L-function is applied to the RSSI received at each time t and for each of the location anchors. In this case, a value close to 1 indicates higher proximity to the location anchor. The proximity membership function is defined as follows:

$$L - FProximity(RSSI) : TS(-95, -85)$$

The second level establishes a fuzzy time window size defined by a trapezoidal membership L-function applied in this case to the values between 0 and 1 obtained in the first level. The membership function defined is the following:

$$L - FTemporalWindow(\Delta t) : TS(5, 3)$$

This membership function gives more importance to closer samples (3 seconds or less) and less importance to samples further away (4 to 5 seconds). Therefore, at each instant t a temporal window of at most 5 seconds is constructed with the output of the first level, and for each sample the output of the second level is applied as a multiplicative factor, depending on the distance of the sample in seconds.

Finally, for each location anchor, an arithmetic mean of the values obtained in the time window is taken and its relevant location is established. If there is more than one anchor in the same location, as in the case of the bedroom, another arithmetic mean is performed with the final results of each anchor. Finally, the inferred location at that instant t corresponds to the maximum of the relevant locations.

For the detection of daily activities, a fuzzy methodology has been established based on the work of M.A. López-Medina et al. [57]. For each daily activity, a series of linguistic protoforms based on expert knowledge and fuzzy logic have been defined. For example, the following rule has been defined for the daily activity of sleeping:
$RSleeping : relevant\ location\ is\ bedroom$
$AND\ low\ movement\ in\ bed$
$AND\ low\ activity\ inhabitant$

In this case, the rule makes use of the current detected location and a number of fuzzy sets: movement in bed and the inhabitant's overall activity level as a function of the activity wristband. In both cases, two types of movement or activity are established: low and high.

Membership functions for activity and movement in bed are defined as:

- $R - LowMovement(activations) : TS(1, 5)$
- $L - HighMovement(activations) : TS(0, 10)$
- $R - LowActivity(steps) : TS(10, 30)$
- $L - HighActivity(steps) : TS(0, 100)$

The associated membership functions are defined in Figure 5 and Figure 4.

[7]https://www.tp-link.com/es/home-networking/adapter/ub400

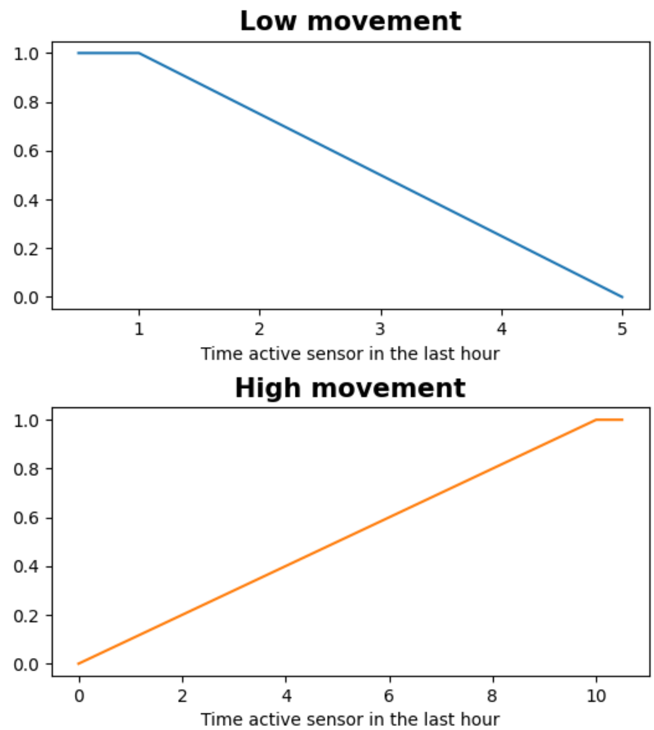

FIGURE 4. **Trapezoidal membership functions defined for bed movement**

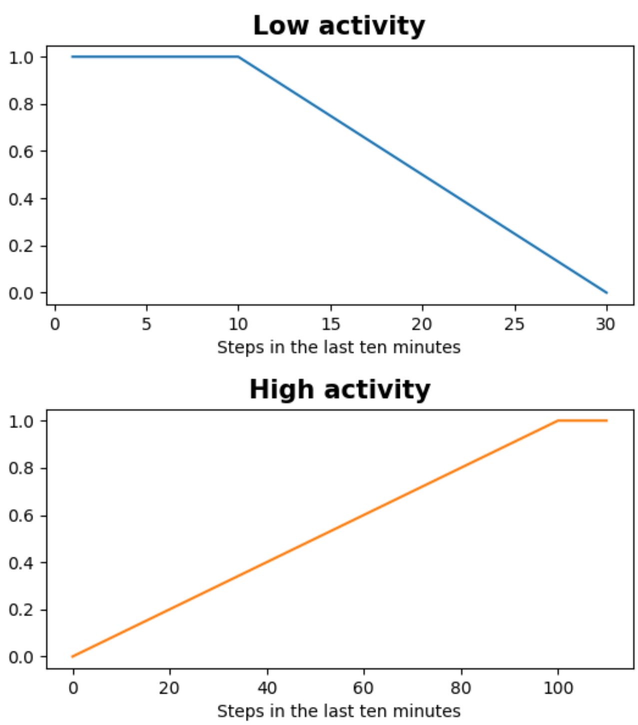

FIGURE 5. **Trapezoidal membership functions defined for inhabitant activity**

The other protoforms and membership functions established for the recognition of the activities are set out below.

Protoforms:

- $RDressing$: *relevant location is bedroom AND recent interaction with the wardrobe*
- $RShowering$: *relevant location is bathroom AND motion in the shower area AND shower head vibrates.*
- $RUsingToilet$: *relevant location is bathroom AND motion in the toilet area*
- $RExitRoom$: *relevant location is outside AND stay out of the room*

Membership functions:

- $R - FRecentInteractionWardrobe(seconds) : TS(0, 15)$
- $R - FMotionShower(seconds) : TS(10, 30)$
- $R - FVibrationShowerHead(minutes) : TS(1, 2)$
- $R - MotionToilet(seconds) : TS(0, 30)$
- $L - StayAtRoom(minutes) : TS(0, 5)$
- $L - StayOutside(minutes) : TS(0, 3)$

For membership functions whose inputs are minutes and seconds, the entry data is the time difference between the current time t and the last time the sensor was activated.

E. ACTIVA APP FOR CAREGIVERS

This section presents the mobile application ACTIVA, designed to be used by social and health care staff to monitor inhabitants. Its features include the monitoring of several inhabitants, which means it supports multi-occupancy environments, as well as real-time monitoring. This software is composed of two main views, illustrated in Figure 6.

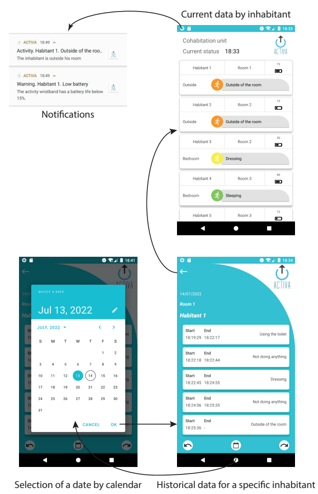

FIGURE 6. **ACTIVA mobile application for monitoring the location and daily activities of nursing home inhabitants.**

The first view shown in Figure 7 shows all the monitored inhabitants and displays the most important information about each of them in real time.

For each inhabitant, the battery percentage of the associated activity wristband is shown in the top right part and the

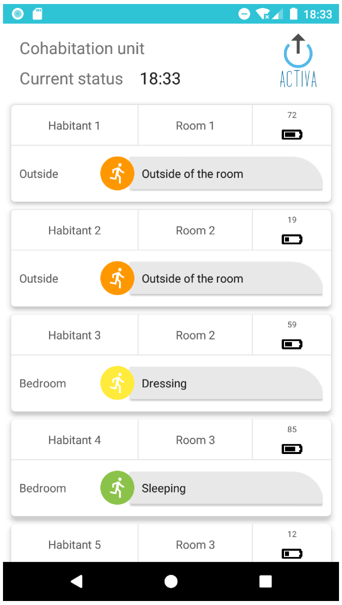

FIGURE 7. Current data by inhabitant.

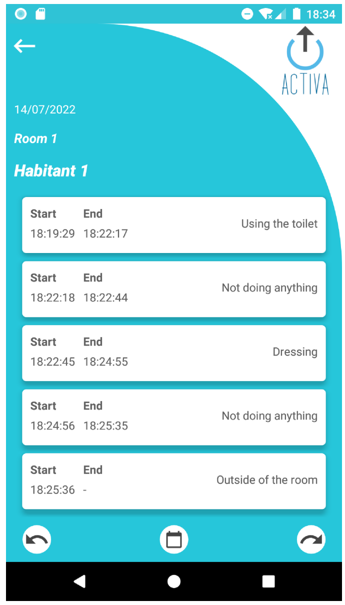

FIGURE 8. Historical data for a specific inhabitant.

last detected activity and location is displayed in the bottom. In addition, depending on the danger level of the activity being carried out by the inhabitant, it will have a different colour. The possible colours are green (low danger), yellow (medium danger) and orange (high danger). For example, in Figure 7 inhabitant 3, whose room is number 2, is shown to be in the bedroom performing the activity ''dressing'', which has a yellow colour indicating medium danger. Sleeping would be a low danger, leaving the room and showering would be a high danger, and using the toilet and dressing would be a medium danger.

If the caregiver wants to see information on an inhabitant, they can click on that inhabitant and the second view will appear, which is shown in Figure 8.

In the second view (Figure 8), a history of the daily activities detected on a specific day is shown for each inhabitant. The activities are sorted in chronological order and for each activity a start and end timestamp is indicated. Likewise, the caregiver can view any other period in two ways:

- Through the calendar icon. Located in the middle of the lower panel. In this new view, a calendar will appear to choose the day and month (Figure 9).
- Through the arrow icons. Located at the left and right ends of the lower panel.

In addition, as shown in Figure 10, the ACTIVA mobile application is constantly running in the background and receives notifications with any relevant changes. For example, if the battery of the activity wristband is too low.

It is worth mentioning that, in any case, neither the inhabitants' real names nor any information that could identify them in the event of a cyberattack are provided in order to guarantee their anonymity.

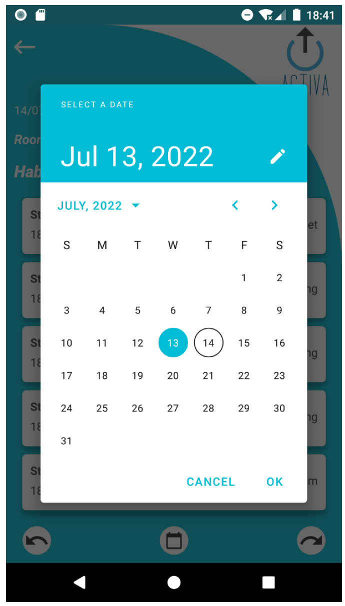

FIGURE 9. Calendar.

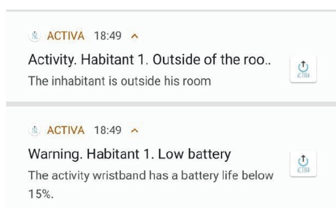

FIGURE 10. Notifications.

Finally, it should be noted that the ACTIVA mobile application has software intellectual property protection [12].

IV. EVALUATION OF THE IMPACT OF THE ACTIVA SYSTEM

This section presents the evaluation of the ACTIVA system. For this purpose, a 53-question survey was carried out with 23 participants for each profile (caregivers, elderly residents, family members, director of the nursing home and social and health care professionals).

A. CAREGIVERS

The quantitative questions chosen for the caregiver profile are shown in Table 2 below.

TABLE 2. Quantitative questions for the caregiver.

Point of view of the caregiver as direct beneficiary
1. Does the mobile app help reduce stress at work?
2. Does the mobile app help to increase safety in the treatment and care of the residents?
3. Does the mobile app help understand the behaviour of the residents andis it useful for your work?
4. Does the mobile app help provide more personalised care?
5. Does the mobile app improve quality of life at work?

The answers to these questions from the participants in the caregiver profile (Figure 11) were mostly positive: 48% of the caregivers find the mobile application very useful because it reduces stress at work and 52% believe that the mobile application is excellent to better understand the behaviour of the inhabitants, as well as being useful for their work. A large percentage of the participants also believe that the app helps provide personalised care (44%) and would be useful for increasing the safety of care (48%) and the quality of life of the worker (44%).

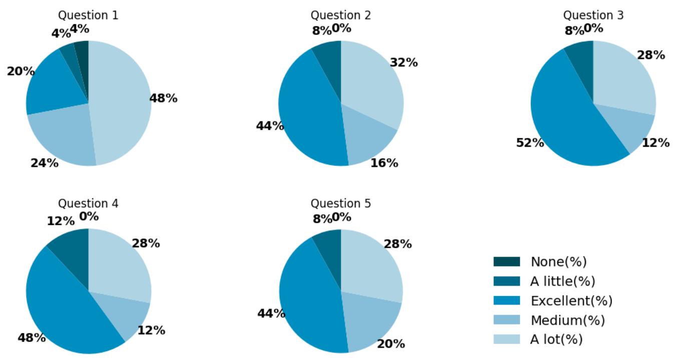

FIGURE 11. Quantitative questions for the caregivers as a direct beneficiary.

B. ELDERLY RESIDENTS

This section shows the quantitative questions used for the elderly resident profile as direct beneficiaries in the Table 3 below.

TABLE 3. Quantitative questions for the elderly resident.

Point of view of the elderly resident as a direct beneficiary
1. Have you felt intimidated by the sensors deployed in the nursing home?
2. Do you think the technology is transparent and you should not interact with it?
3. Do you feel safer knowing that any anomaly will be reported?
4. Do you think the benefits of the system are greater than the privacy-related drawbacks?
5. Would you like to have this system in your nursing home?

The answers collected by the participants to the questions in the Table 3 are shown in Figure 12.

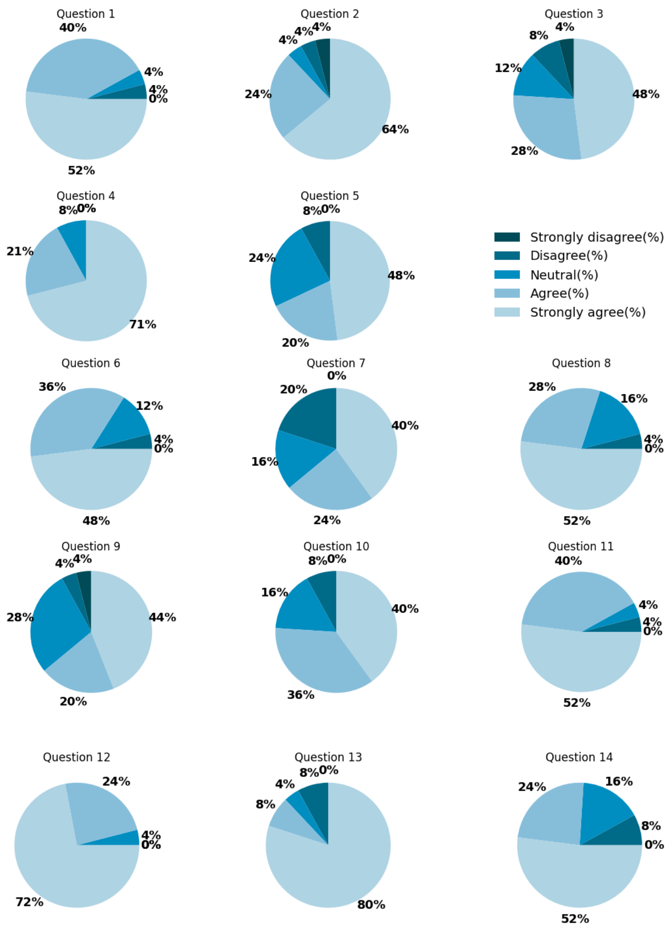

FIGURE 12. Quantitative questions for the elderly resident as a direct beneficiary.

The answers collected show that 56% of the participants do not believe that the use of sensors intrudes on their privacy. Furthermore, it is clear from the rest of the questions that a high percentage of the participants find the technology transparent, with the system being beneficial in helping to increase the safety of the residents. And even 52% strongly agree that the benefits outweigh the disadvantages in terms of privacy and 64% of the answers strongly agree to having such a system deployed in their nursing home.

C. OTHER STAKEHOLDERS

This section shows the quantitative questions posed for the following profiles: family member, director of the nursing home, and social and health care professional.

1) Family member

First, the following Table 4 shows the quantitative questions for family members.

TABLE 4. Quantitative questions for the family member.

Point of view of the the family member
1. If you had a relative in the nursing home, would you like to know their behaviour in the nursing home?
2. If you had a relative in the nursing home, would you like to know how much time they rest in bed?
3. If you had a relative in the nursing home, would you like to know the number of times they go to the toilet during the day?
4. If you had a relative in the nursing home, would you like to know if they shower and wash themselves?
5. If you had a relative in the nursing home, would you like to know the number of daily steps taken by them?
6. If you had a relative in the nursing home, would you like to know how many times they get up at night?
7. If you had a relative in the nursing home, would you like to know how many minutes they lie in bed?
8. If you had a relative in the nursing home, would you like to know how long they spend in the bathroom?
9. If you had a relative in the nursing home, would you like to know how much time they spend out of their room?
10. If you had a relative in the nursing home, would you like to know how much time they spend eating?
11. If you had a relative in the nursing home, would you like to know how much time they spend outside?
12. If you had a relative in the nursing home,would you like to know how much time they spend in therapy?
13. If you had a relative in the nursing home, would you like to know how much time they spend alone?
14. If you had a relative in the nursing home, would you like to know how much time they spend with other people?

The results obtained for the participants in the family member profile (Figure 13) show they would mainly like to receive notifications about: time spent alone (80%), time spent with other people (76%), time spent in therapy (72%), whether they shower/wash themselves every day (68%) and the amount of time resting in bed (64%).

While to a lesser extent they would like to have notifications about: the behaviour of the elderly resident (52%), how many times they go to the toilet per day (48%), the number of daily steps (48%), how many times they get up at night (48%), time spent lying in bed (40%), time spent on the toilet (52%), time spent out of the room (44%), time spent eating (40%) and time spent in therapy (52%).

So overall it can be seen that acceptance among this profile is also positive, as the answers of the participants who

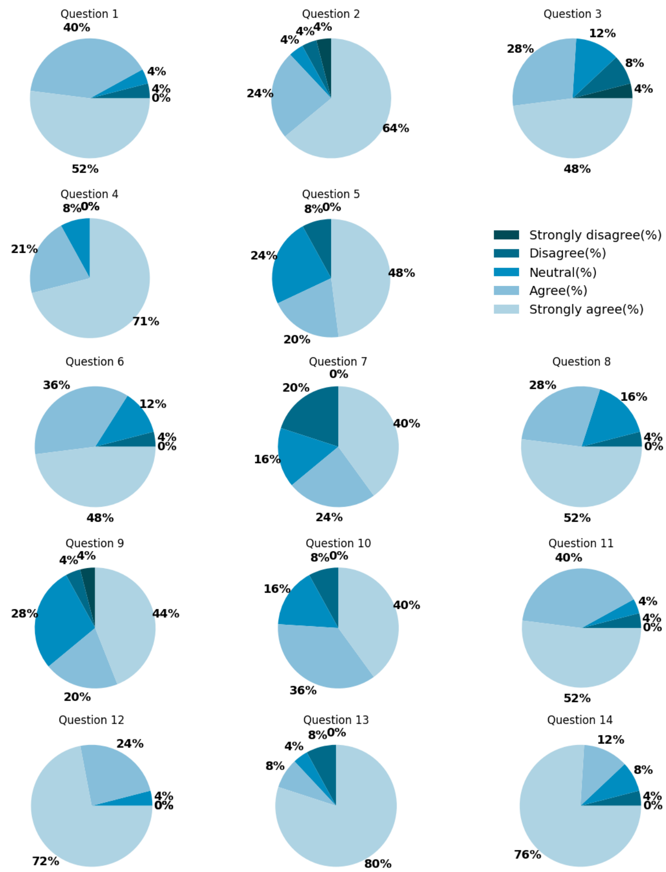

FIGURE 13. Quantitative questions for the family member.

strongly agree are either around half or more than half of the total.

2) Director of a nursing home

The following Table 5 shows the quantitative questions for the nursing home director profile, which, as can be seen, are the same as the previous ones that were asked to the family member profile.

The answers given in the profile of the nursing home director (Figure 14) show that they would most like to have notifications about: time spent in therapy (72%), time spent alone (68%), time spent with other people (68%), time spent outdoors (64%), if they shower/wash themselves every day (63%) and the behaviour of the residents in the nursing home (60%).

While to a lesser extent they would like to have notifications about: time spent in bed (52%), how many times they go to the toilet per day (44%), the number of daily steps (44%), how many times they get up at night (56%), time spent lying in bed (40%), time spent in the bathroom (52%), time spent outside the room (44%) and time spent eating (44%).

TABLE 5. Quantitative questions for the director of a nursing home.

Point of view of the director of a nursing home.
1. As the director of a nursing home, would you like to know the behaviour of the residents?
2. As the director of a nursing home, would you like to know how much time the residents rest in bed?
3. As the director of a nursing home, would you like to know the number of times the residents go to the toilet during the day?
4. As the director of a nursing home, would you like to know if the residents shower and wash themselves?
5. As the director of a nursing home, would you like to know the number of daily steps taken by the residents?
6. As the director of a nursing home, would you like to know how many times the residents get up at night?
7. As the director of a nursing home, would you like to know how many minutes the residents lie in bed?
8. As the director of a nursing home, would you like to know how much time the residents spend in the bathroom?
9. As the director of a nursing home, would you like to know how much time the residents spend outside their room?
10. As the director of a nursing home, would you like to know how much time the residents spend eating?
11. As the director of a nursing home, would you like to know how much time the residents spend outside?
12. As the director of a nursing home, would you like to know how much time the residents spend in therapy?
13. As the director of a nursing home, would you like to know how much time the residents spend alone?
14. As the director of a nursing home, would you like to know how much time the residents spend with other people?

Again, in general, like the family member profile, the system is also well accepted among directors, as the answers of the participants who strongly agree are either around half or exceed half of the total.

3) Social and health care professionals

Finally, the questions (Table 6) from the survey that were answered by social and health care professionals are shown. These questions ask whether social and health care professionals would recommend the ACTIVA system for settings other than a nursing home.

The answers collected in these responses, shown in Figure 15 , highlight that the majority of the participants would recommend the use of this system by a strong percentage for: management of supervised flats for people with disabilities (80%) and home of an elderly family member living alone (80%).

In general, the participants would also recommend the use of this system to other professionals in the sector they were asked about.

Finally, 64% of the participants felt that if family members had access to the activities their elderly relative was engaged in, they would also have more extensive topics to discuss.

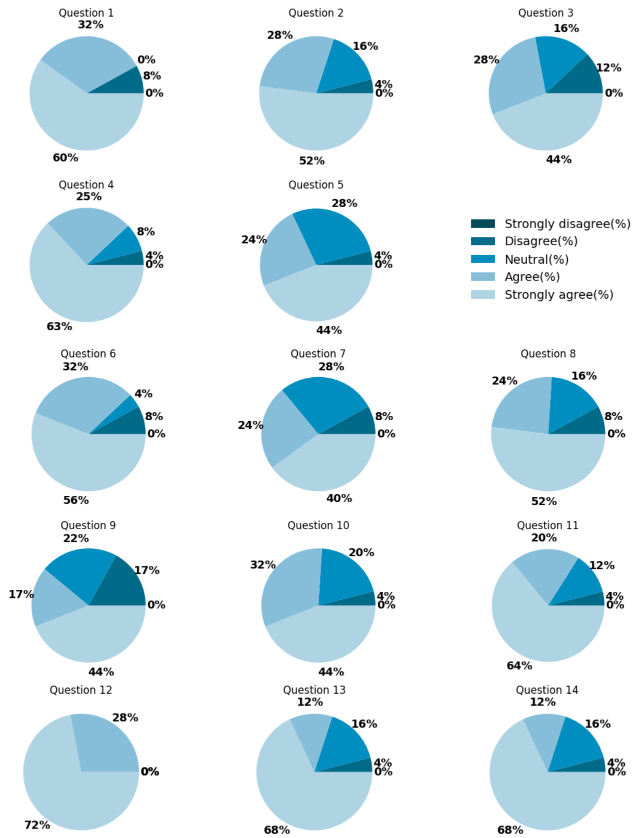

FIGURE 14. Quantitative questions for the nursing home director.

TABLE 6. Quantitative personal opinion questions

Quantitative personal opinion questions
1. Do you think the benefits of the system are greater than the privacy-related drawbacks?
2. Would you like to use this system if you lived in a nursing home?
3. Would you recommend this system to a nursing home manager?
4. Would you recommend this system to a family member of an elderly person living in a nursing home?
5. Would you recommend this system to a supervisor of flats where people with disabilities live?
6. Would you recommend this system to a family member of a person living in a flat for people with disabilities?
7. Would you recommend this systemto a family member of an elderly couple living alone?
8. Would you recommend this system to an elderly couple living alone?
9. Would you recommend this system to the health system manager in order to know the capabilities of the elderly?
10. Would you recommend this system to a manager of home care services in order to know the capabilities of the elderly under care?
11. Would you recommend this system to a home care manager to know the tasks carried out by the caregivers?
12. Studies show family members, who have access to the elderly's activities, have longer conversations with their relatives. Have you ever thought about this benefit?

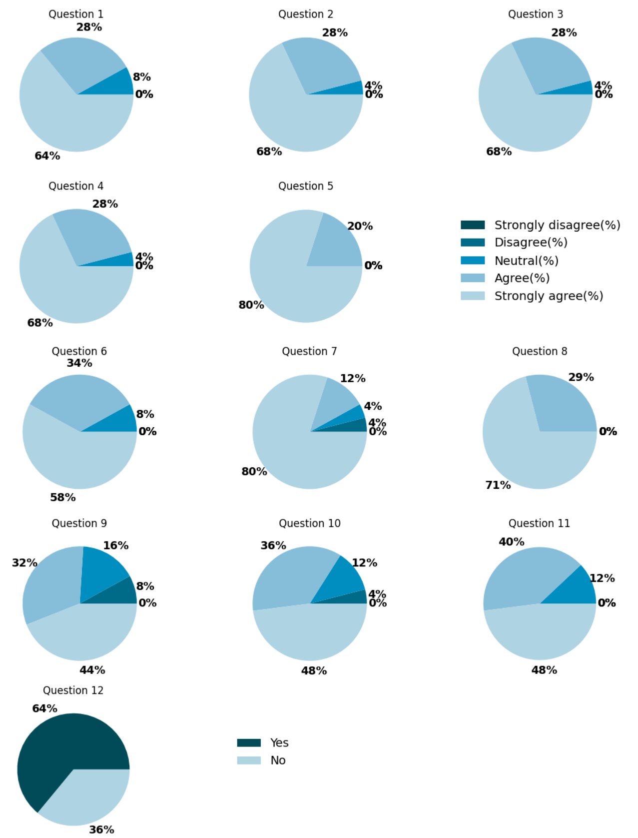

FIGURE 15. **Quantitative personal opinion questions.**

4) Qualitative questions

Apart from the quantitative questions, qualitative questions were asked to all the different stakeholders (caregivers, elderly residents, family members, nursing home directors and social and health care professionals). The answers to the qualitative questions are shown below:

- **Question 1. What other activities would you recommend to include?**
  Answers: Include more specific health variables such as blood pressure, glucose or oxygen levels; monitor the time the elderly person spends on leisure activities, improvement of cognitive abilities and visits to the social and health care professional, psychologist and physiotherapist; find out the closest contacts between inhabitants to know with whom they feel more comfortable; detection of possible falls or voice detection to know if they are calling for help.
- **Question 2. List the positive aspects of the system**
  Answers: The participants highlight the improvement of the quality of life of elderly people as the main objective, as well as the thorough control of the residents, providing more security, helping to prevent certain incidents and giving the family members greater peace of mind. Additionally, providing a more personal approach to care while reducing the workload on caregivers.
- **Question 3. List the negative aspects of the system.**
  Answers: The participants pointed to disadvantages such as the possible lack of privacy, the lack of knowledge or distrust of this new technology by users of the application, the costs involved in the deployment of the system, or the misreading of data by application users.

V. CONCLUSIONS

This paper presents the ACTIVA system, an activity recognition system deployed in a nursing home with the aim of improving the safety of elderly residents and reducing the workload stress of caregivers. The ACTIVA system consists of a set of sensors that use fuzzy logic techniques, linguistic protoforms, and temporal windows to infer the location and activity of each inhabitant in a multi-occupancy environment.

The system is composed of a fog-cloud architecture, where each shared room in the nursing home has a fog node that collects all the information from that room, and sends it to a cloud platform where location and activity inference is performed. A mobile application for the caregivers of the nursing home connects to the cloud platform to monitor and supervise the residents, receiving real-time notifications of any anomalies.

The paper has presented an integrated evaluation of the ACTIVA system in a nursing home setting. The results of the surveys show a generally positive view and acceptance of the ACTIVA system from all the different stakeholders (caregivers, elderly residents, family members, nursing home directors, and social and health care professionals). They highlighted that this system would improve the quality of life of the elderly residents and could help to reduce the workload and stress of the caregivers while providing more personalized care. However, survey participants also noted certain negative aspects that need to be taken into account, such as potential misuse by application users, concerns about privacy, and possible problems when using these technologies due to the existing technological and generational gaps.

REFERENCES

[1] Ageing and health. [Online]. Available: https://www.who.int/es/news-room/fact-sheets/detail/ageing-and-health
[2] J. Dumurgier and C. Tzourio, "Epidemiology of neurological diseases in older adults," *Revue Neurologique*, vol. 176, no. 9, pp. 642–648, 2020.
[3] A. Chan, M. Tamrakar, C. Jiang, E. Lo, K. Leung, and C. Chu, "Common medical and dental problems of older adults: A narrative review," *Geriatrics*, vol. 6, no. 3, p. 76, 2021.
[4] J. Cacioppo and S. Cacioppo, "The growing problem of loneliness," *The Lancet*, vol. 391, no. 10119, p. 426, 2018.
[5] C. Park, A. Majeed, H. Gill, J. Tamura, R. C. Ho, R. B. Mansur, F. Nasri, Y. Lee, J. D. Rosenblat, E. Wong *et al.*, "The effect of loneliness on distinct health outcomes: a comprehensive review and meta-analysis," *Psychiatry Research*, vol. 294, p. 113514, 2020.
[6] N. Cotterell, T. Buffel, and C. Phillipson, "Preventing social isolation in older people," *Maturitas*, vol. 113, pp. 80–84, 2018.
[7] N. Kandelman, T. Mazars, and A. Levy, "Risk factors for burnout among caregivers working in nursing homes," *Journal of Clinical Nursing*, vol. 27, no. 1-2, pp. e147–e153, 2017.
[8] E. White, L. Aiken, D. Sloane, and M. McHugh, "Nursing home work environment, care quality, registered nurse burnout and job dissatisfaction," *Geriatric Nursing*, vol. 41, no. 2, pp. 158–164, 2020.

[9] C. Jobanputra, J. Bavishi, and N. Doshi, "Human activity recognition: A survey," *Procedia Computer Science*, vol. 155, pp. 698–703, 2019.
[10] R. Hamad, A. Salguero, M. Bouguelia, M. Espinilla, and J. Medina, "Efficient activity recognition in smart homes using delayed fuzzy temporal windows on binary sensors," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 2, pp. 387–395, 2020.
[11] M. Espinilla, J. Medina, J. Hallberg, and C. Nugent, "A new approach based on temporal sub-windows for online sensor-based activity recognition," *Journal of Ambient Intelligence and Humanized Computing*, 2018.
[12] M. Espinilla, J. Medina, M.A. Verdejo, J.L Ruiz and A.G. Salguero. (2021) ACTIVA. [Online]. Available: https://www.safecreative.org/work/2111159810407
[13] M. López, M. Espinilla, I. Cleland, C. Nugent, and J. Medina, "Fuzzy cloud-fog computing approach application for human activity recognition in smart homes," *Journal of Intelligent &Fuzzy Systems*, vol. 38, no. 1, pp. 709–721, 2020.
[14] M. Espinilla, L. Martinez, J. Medina, and C. Nugent, "The experience of developing the UJAmI smart lab," *IEEE Access*, vol. 6, pp. 34 631–34 642, 2018.
[15] A. Albín, Y. D. L. Fuente, J. López, M. Verdejo, and M. Espinilla, "UJAmI location: A fuzzy indoor location system for the elderly," *International Journal of Environmental Research and Public Health*, vol. 18, no. 16, p. 8326, 2021.
[16] A. Jimenez, F. Seco, P. Peltola, and M. Espinilla, "Location of persons using binary sensors and BLE beacons for ambient assitive living," in *2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2018.
[17] M. Á. L. Medina, M. Espinilla, C. Paggeti, and J. M. Quero, "Activity recognition for iot devices using fuzzy spatio-temporal features as environmental sensor fusion," *Sensors (Basel, Switzerland)*, vol. 19, no. 16, 2019.
[18] A.-P. Albin, A.-J. Ricoy-Cano, Y.-M. De-La-Fuente-robles, and M. Espinilla, "Fuzzy protoform for hyperactive behaviour detection based on commercial devices," *International Journal of Environmental Research and Public Health*, vol. 17, no. 18, pp. 1–23, 2020.
[19] M. Pelaez-Aguilera, M. Espinilla, M. Fernandez Olmo, and J. Medina, "Fuzzy linguistic protoforms to summarize heart rate streams of patients with ischemic heart disease," *Complexity*, vol. 2019, 2019.
[20] M. López, M. Espinilla, C. Paggeti, and J. Medina, "Activity recognition for IoT devices using fuzzy spatio-temporal features as environmental sensor fusion," *Sensors*, vol. 19, no. 16, p. 3512, 2019.
[21] E. De-La-Hoz-Franco, E. Bernal-Monroy, P. Ariza-Colpas, F. Mendoza-Palechor, and M. Espinilla, "UJA human activity recognition multi-occupancy dataset," in *Proceedings of the Annual Hawaii International Conference on System Sciences*. Hawaii International Conference on System Sciences, 2021.
[22] E. D. L. Hoz, P. Ariza-Colpas, J. Medina, and M. Espinilla, "Sensor-based datasets for human activity recognition – a systematic review of literature," *IEEE Access*, vol. 6, pp. 59 192–59 210, 2018.
[23] M. Espinilla, J. Medina, A. Calzada, J. Liu, L. Martínez, and C. Nugent, "Optimizing the configuration of an heterogeneous architecture of sensors for activity recognition, using the extended belief rule-based inference methodology," *Microprocessors and Microsystems*, vol. 52, pp. 381–390, 2017.
[24] J. Medina, L. Martínez, and M. Espinilla, "Subscribing to fuzzy temporal aggregation of heterogeneous sensor streams in real-time distributed environments," *International Journal of Communication Systems*, vol. 30, no. 5, 2016.
[25] Z. Hussain, Q. Sheng, and W. Zhang, "A review and categorization of techniques on device-free human activity recognition," *Journal of Network and Computer Applications*, vol. 167, 2020.
[26] S. Yadav, K. Tiwari, H. Pandey, and S. Akbar, "A review of multimodal human activity recognition with special emphasis on classification, applications, challenges and future directions," *Knowledge-Based Systems*, vol. 223, 2021.
[27] M. Straczkiewicz, P. James, and J. Onnela, "A systematic review of smartphone-based human activity recognition methods for health research," *npj Digital Medicine*, vol. 4, no. 1, 2021.
[28] R. Liang, S. Yang, and B. Chen, "InDexMo," in *Proceedings of the 23rd International Symposium on Wearable Computers*, 2019.
[29] E. Ramanujam, T. Perumal, and S. Padmavathi, "Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review," *IEEE Sensors Journal*, vol. 21, no. 12, pp. 13 029–13 040, 2021.
[30] C. Yu, Z. Xu, K. Yan, Y.-R. Chien, S.-H. Fang, and H.-C. Wu, "Noninvasive human activity recognition using millimeter-wave radar," *IEEE Systems Journal*, vol. 16, no. 2, pp. 3036–3047, 2022.
[31] S.-H. Fang, C.-C. Li, W.-C. Lu, Z. Xu, and Y.-R. Chien, "Enhanced device-free human detection: Efficient learning from phase and amplitude of channel state information," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 3048–3051, 2019.
[32] D. Jha, Z. Chen, S. Liu, M. Wu, J. Zhang, G. Morgan, R. Ranjan, and X. Li, "A hybrid accuracy- and energy-aware human activity recognition model in IoT environment," *IEEE Transactions on Sustainable Computing*, pp. 1–13, 2022.
[33] S. Uday, S. Pavani, T. Lakshmi, and R. Chivukula, "Classifying human activities using machine learning and deep learning techniques," *arXiv preprint arXiv:2205.10325*, 2022.
[34] A. Biswal, S. Nanda, C. Panigrahi, S. Cowlessur, and B. Pati, "Human activity recognition using machine learning: A review," in *Advances in Intelligent Systems and Computing*. Springer, 2021, pp. 323–333.
[35] M. Z. Uddin, M. M. Hassan, A. Alsanad, and C. Savaglio, "A body sensor data fusion and deep recurrent neural network-based behavior recognition approach for robust healthcare," *Information Fusion*, vol. 55, pp. 105–115, 2020.
[36] S. Jindal, M. Sachdeva, and A. Singh, "Deep learning for video based human activity recognition: Review and recent developments," in *Algorithms for Intelligent Systems*. Springer, 2021, pp. 71–83.
[37] R. A. Hamad, A. S. Hidalgo, M.-R. Bouguelia, M. E. Estevez, and J. M. Quero, "Efficient activity recognition in smart homes using delayed fuzzy temporal windows on binary sensors," *IEEE journal of biomedical and health informatics*, vol. 24, no. 2, pp. 387–395, 2019.
[38] D. Zafra, J. Medina, L. Martinez, C. Nugent, and M. Espinilla, "A web system for managing and monitoring smart environments," in *Bioinformatics and Biomedical Engineering*. Springer, 2016, pp. 677–688.
[39] A. Bicharra, A. Santarosa, N. Sanchez, L. Marti, and J. Molina, "Crowd-based ambient assisted living to monitor the elderly's health outdoors," *IEEE Software*, vol. 34, no. 6, pp. 53–57, 2017.
[40] S. Ranasinghe, F. Al, and H. Mayr, "A review on applications of activity recognition systems with regard to performance and evaluation," *International Journal of Distributed Sensor Networks*, vol. 12, no. 8, 2016.
[41] L. M. Dang, K. Min, H. Wang, M. J. Piran, C. H. Lee, and H. Moon, "Sensor-based and vision-based human activity recognition: A comprehensive survey," *Pattern Recognition*, vol. 108, p. 107561, 2020.
[42] M. Boulos, A. Rocha, A. Martins, M. Vicente, A. Bolz, R. Feld, I. Tchoudovski, M. Braecklein, J. Nelson, G. Ó. Laighin, C. Sdogati, F. Cesaroni, M. Antomarini, A. Jobes, and M. Kinirons, "CAALYX: a new generation of location-based services in healthcare," *International Journal of Health Geographics*, vol. 6, no. 1, p. 9, 2007.
[43] P. Ganesh, R. Etemadi, C. Basavanahally, A. Ramesh, and M. Kyrarini, "Personalized system for human gym activity recognition using an RGB camera," in *Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments*, 2020.
[44] L. Bibbo and R. Carotenuto, "An integrated system for indoor people localization, tracking, and monitoring," *Global J., Geneva, Switzerland, Tech. Rep*, vol. 15, 2021.
[45] S. Spinsante, A. Angelici, J. Lundström, M. Espinilla, I. Cleland, and C. Nugent, "A mobile application for easy design and testing of algorithms to monitor physical activity in the workplace," *Mobile Information Systems*, vol. 2016, pp. 1–17, 2016.
[46] I. da Penha, L. Correia, A. Garcia, and L. Fernandes, "Efficient out-of-home activity recognition by complementing GPS data with semantic information," *First Monday*, 2019.
[47] A. Jimenez, F. Seco, P. Peltola, and M. Espinilla, "Location of persons using binary sensors and BLE beacons for ambient assitive living," in *2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2018.
[48] A. Verdejo, J. L. Lopez, F. Mata, and M. Espinilla, "Application of IoT in healthcare: Keys to implementation of the sustainable development goals," *Sensors*, vol. 21, no. 7, p. 2330, 2021.
[49] A. Verdejo, M. Espinilla, J. López, and F. Jurado, "Assessment of sustainable development objectives in smart labs: technology and sustainability at the service of society," *Sustainable Cities and Society*, vol. 77, p. 103559, 2022.
[50] K. Kim, A. Jalal, and M. Mahmood, "Vision-based human activity recognition system using depth silhouettes: A smart home system for monitoring the residents," *Journal of Electrical Engineering & Technology*, vol. 14, pp. 2567–2573, 2019.

[51] H. Ramirez, S. A. Velastin, I. Meza, E. Fabregas, D. Makris, and G. Farias, "Fall detection and activity recognition using human skeleton features," *Ieee Access*, vol. 9, pp. 33 532–33 542, 2021.

[52] Eclipse Foundation, Inc. Eclipse Mosquitto broker. [Online]. Available: https://mosquitto.org/

[53] S. Farahani, "ZigBee and IEEE 802.15.4 protocol layers," in *ZigBee Wireless Networks and Transceivers*. Elsevier, 2008, pp. 33–135.

[54] Nabu Casa. Home Assistant. [Online]. Available: https://www.home-assistant.io/

[55] B. Lashkari, J. Rezazadeh, R. Farahbakhsh, and K. Sandrasegaran, "Crowdsourcing and sensing for indoor localization in IoT: A review," *IEEE Sensors Journal*, vol. 19, no. 7, pp. 2408–2434, 2019.

[56] B. Wang, Q. Chen, L. Yang, and H. Chao, "Indoor smartphone localization via fingerprint crowdsourcing: challenges and approaches," *IEEE Wireless Communications*, vol. 23, no. 3, pp. 82–89, 2016.

[57] M. López-Medina, M. Espinilla, I. Cleland, C. Nugent, and J. Medina, "Fuzzy cloud-fog computing approach application for human activity recognition in smart homes," *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 1, pp. 709–721, 2020.

ALICIA MONTORO LENDÍNEZ obtained the degree in Industrial Electronic Engineering and the Master Degree in Mechatronics Engineering from the University of Jaén, in 2020 and 2022 respectively, where she is currently pursuing her PhD in Information and Communication Technologies. She is currently a member of the ASIA research group (Advances in Intelligent Systems and Applications) at the University of Jaén. Her current research interests are the Internet of Things, ambient assisted living and machine learning.

JOSÉ LUIS LÓPEZ RUIZ was born in Linares (Jaén), Spain, in 1993. He received his M.Sc. and Ph.D. degrees, both in Computer Science from the University of Jaén (Jaén, Spain) in 2020 and 2023, respectively. Currently, he is assistant professor at the University of Jaén in the Department of Computer Science. His current research interests are Internet of Medical Things, ambient assisted living, indoor location systems and sustainability.

CHRIS NUGENT (Member, IEEE) is currently the Head of the School of Computing at Ulster University, Newtownabbey, U.K., where he also leads the Pervasive Computing Research Centre. His research addresses the themes of the development and evaluation of technologies to support pervasive healthcare within smart environments. Specifically, this has involved research in the topics of mobile-based reminding solutions, activity recognition, and behavior modeling and more recently technology adoption modeling.

MACARENA ESPINILLA ESTÉVEZ was born in 1983 in Jaén, Spain. She holds an M.Sc. and Ph.D. in Computer Science, both from the University of Jaén, Spain, awarded in 2006 and 2009, respectively. In recognition of her outstanding work, she received the extraordinary award for her Ph.D. in 2015. Currently, she serves as a Full Professor in the Computer Science Department at the University of Jaén and is the responsible leader of the research group ASIA (Avances en Sistemas Inteligentes y Aplicaciones), which focuses on advancements in intelligent systems and applications. She has made significant contributions to the field of activity recognition for improving the quality of life for individuals. In 2022, her remarkable achievements led her to receive a medal in the Young Researchers Awards by the Royal Academy of Engineering in Spain. Her research interests primarily revolve around eHealth, ambient intelligence, ambient assisted living, and activity recognition. She has published over 50 papers in SCI-indexed journals and serves as a member of the editorial board for the Journal of Universal Computer Sciences, IEEE Access, and the Journal of Sensor and Actuator Networks.