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ACTIVE AGING IN PLACE SUPPORTED BY A CAREGIVER-CENTERED MODULAR LOW-COST PLATFORM

Dissertação para obtenção do Grau de Mestre em
Engenharia de Software

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março, 2021

To my grandparents

Acknowledgements

Since it makes perfect sense, I will start by thanking my grandparents.

I also want to thank my whole family, for their support, affection, motivation, and with the certainty that without them, nothing would be possible.

Following this, I would like to thank all the teachers who directly or indirectly followed my academic journey, with the certainty that they all gave their contribution to make me a better professional, not only for the teaching and transmission of knowledge, but mainly for the exigency, discipline and challenges that provided me with the basis to acquire the capacity to learn for myself.

A special appreciation to my advisors, Prof. Rui Madeira and Prof. Patrícia Macedo for the challenge they instilled in me, accompaniment, professionalism and rigour. They were a key piece in my academic journey and made me believe it was possible.

Last but not least, I would like to thank my girlfriend for the way she is present in my life, because without her love, unconditional support and perseverance the achievement of this goal would be unattainable.

Abstract

Aging in place happens when people age in the residence of their choice, usually their homes because is their preference for living as long as possible. This research work is focused on the conceptualization and implementation of a platform to support active aging in place with a particular focus on the caregivers and their requirements to accomplish their tasks with comfort and supervision. An engagement dimension is also a plus provided by the platform since it supports modules to make people react to challenges, stimulating them to be naturally more active. The platform is supported by IoT, using low-cost technology to increment the platform modularly. Is a modular platform capable of responding to specific needs of seniors aging in place and their caregivers, obtaining data regarding the person under supervision, as well as providing conditions for constant and more effective monitoring, through modules and tools that support decision making and tasks realization for active living. The constant monitoring allows knowing the routine of daily activities of the senior. The use of machine learning techniques allows the platform to identify, in real-time, situations of potential risk, allowing to trigger triage processes with the older adult, and consequently trigger the necessary actions so that the caregiver can intervene in useful time.

Keywords: Ambient Assisted Living, Aging in Place, Active Aging, Pervasive Computing, HCI, Context-Awareness, Daily Activity Routine, Real-Time Location Systems, Caregiver, Modular Platform.

Sumário

O envelhecimento no local acontece quando as pessoas envelhecem na residência da sua escolha, geralmente nas suas próprias casas porque é a sua preferência para viver o máximo de tempo possível. Este trabalho de investigação foca-se na conceptualização e implementação de uma plataforma de apoio ao envelhecimento ativo no local, com particular enfoque nos cuidadores e nas suas necessidades para cumprir as suas tarefas com conforto e supervisão. Uma dimensão de engajamento também é um diferencial da plataforma, pois esta integra módulos de desafios para fazer as pessoas reagirem aos mesmos, estimulando-as a serem naturalmente mais ativas. A plataforma é suportada por IoT, utilizando tecnologia de baixo custo para incrementar a plataforma de forma modular. É uma plataforma modular capaz de responder às necessidades específicas do envelhecimento dos idosos no local e dos seus cuidadores, obtendo dados relativos à pessoa sob supervisão, bem como fornecendo condições para um acompanhamento constante e mais eficaz, através de módulos e ferramentas que apoiam a tomada de decisões e realização de tarefas para a vida ativa. A monitorização constante permite conhecer a rotina das atividades diárias do idoso, permitindo que, com a utilização de técnicas de *machine learning*, a plataforma seja capaz de detetar em tempo real situações de risco potencial, permitindo desencadear um processo de triagem junto do idoso, e consequentemente despoletar as ações necessárias para que o prestador de cuidados possa intervir em tempo útil.

Palavras-chave: Assistência à Autonomia no Domicílio, Envelhecimento no Local, Envelhecimento Ativo, Computação Pervasiva, Interação Pessoa-Máquina, Contexto Computacional, Atividade Quotidiana, Sistemas de Localização em Tempo Real, Cuidador, Plataforma Modular.

Contents

List of Figures

List of Tables

Acronyms and Symbols

AAL	Active Assisted Living
AI	Artificial Intelligence
ANN	Artificial Neural Networks
API	Application Programing Interface
BaaS	Backend-as-a-Service
BLE	Bluetooth Low Energy
CRUD	Create, Read, Update and Delete
GUI	Graphical User Interface
HCI	Human–Computer Interaction
HTTP	HyperText Transfer Protocol
IaaS	Infrastructure as a Service
IDF	Inverse Document Frequency
INE	Instituto Nacional de Estatística
IoT	Internet of Things
ML	Machine Learning
NIST	National Institute of Standards and Technology
NLP	Natural Language Processing
NUI	Natural User Interface
ORM	Object-Relational Mapping
PaaS	Platform as a Service
PADR	Participatory Action Design Research
REST	Representational State Transfer
RFID	Radio-Frequency Identification
RPC	Remote Procedure Call
RSSI	Received Signal Strength Indicator
RTLS	Real-Time Locating Systems
SaaS	Software as a Service
SSA	Singular Spectrum Analysis
SSID	Service Set IDentifier
TF	Term Frequency
TF-IDF	Term Frequency-Inverse Document Frequency
Tx	Transmission power
URI	Uniform Resource Identifier
UUID	Universally Unique IDentifier
UWB	Ultra-WideBand
W3C	World Wide Web Consortium
WHO	World Health Organization

1

Introduction

Whether national or international, the population has been suffering significant alterations during the last decades, due to the increase of the average lifespan, along with the decrease of the birth rate. These variables have been leading to an older population, with a tendency to increase (Nunes, 2018).

The population's aging brings many challenges around the life quality to the older adults and their caregivers, which is why is necessary to start fighting in the present to obtain efficient solutions for the future. Here, the technology progress may have a crucial part in the development of solutions that can support not only the older adult-caregiver dependency, but also provide ways to promote the older adults' integration in the active life, their mobility, and access to health care, fight the loss of cognitive capacities and even stimulate their autonomy (Sixsmith & Gutman, 2013). In a simple way, keep them healthy and as an active part of society.

1.1. Motivation

The lifestyle of the major part of the population in Portugalnati, due to the daily stress, professional responsibilities, and, many times, the displacement of their homeland increased the older population's distance.

With the tendency to increase, in general, people face many difficulties to adequately support their older family members' daily needs, leading to the latter's isolation (Lopes & Matos, 2018), in the most extreme cases. The natural aging process, by itself, leads inevitably to our elders' isolation when their partners die (Bermejo Higuera, 2016), forcing them to develop a greater autonomy to ensure an independent life, autonomy which, by nature, will decrease.

The development of a technological solution to remote monitoring and assistance to the older adult by a caregiver, who may not be family members, but an institution, would not only contribute to the maintenance of the active life of these people in the community, but also for their independence, remaining in their own houses instead of being institutionalized.

Apart from the social context, the economic factor may also be problematic with regard to the support provided (INE, 2019). The lack of investment power is a significant factor in the efficiency of monitoring the safety and well-being of the older adult at a distance, being that the existing solutions for this purpose are expensive, which is inaccessible for a large part of the population. Thus, it would be extremely important to reduce costs to provide a service that meets the needs and characteristics of the population.

1.2. Problem

The role of caregiver that a person assumes, integrated into her/his active life, whether being a family member or a professional, becomes complex to be effectively performed (Sousa, L., Figueiredo, D. e Cerqueira, 2004). There is a set of systems and platforms developed with the purpose to monitor certain aspects of the daily routine and/or health of the older adult (Pinto et al., 2017), and even some projects that promote the distribution of the effort of this task amongst caregivers, so, in a collaborative way, greater and better monitoring of the older adult can be achieved. However, all these projects are focused mainly on the older adult and few are the ones dedicated to the direct support of the caregivers, to assist them in the performance of their important task.

Moreover, is quite challenging to contour the considerable need for investment in infrastructures and equipment required to assemble a complete platform that attends the older adult's monitoring needs and daily routine.

However, over the last few years, the smart devices[1] and wearables[2]' evolution has been feeding the increasing tendency of the Internet of Things (IoT) concept (Santhi Sri et al., 2016), that is characterized for the connectivity's constant maintenance among different types of ordinary objects in everyday life. The substantial investment in this sector, which is starting to become very

[1] A smart device is an electronic device, usually connected to other devices or networks through different wireless protocols such as Bluetooth, Zigbee, NFC, Wi-Fi, LiFi, 3G, etc., which can work to some extent interactively and autonomously.

[2] Wearables are technologies that come in the form of devices that are the same or similar to pieces of clothing or wearable equipment, such as watches, bracelets or even glasses.

competitive, has been cooperating to the development of these devices in our everyday lives, with already validated technology and usability, low cost and, consequently, making them accessible for most of the social classes (Ciuffoletti, 2018).

With the emergence of this concept, there was a massive appearance of a set of technology and devices, dispersed and independent of each other, easy to use for specific and determined purposes, but that become complex to manage when in excess or in parallel. Once the technology exists and is introduced in the market, it would be convenient to conceive a simple way to cross these devices, making it possible to manage as a whole and, collaboratively, generate useful and complete resources.

1.3. Research Questions and Goal

Considering the exposed problem and objectives, this dissertation proposes to answer the following questions:

> [RQ_A] *Using the existing devices and technology, is it possible to design a platform to provide to the caregiver a set of tools that facilitates their task of supporting the older adult?*

Responding positively to the first premise, the following questions are also formulated:

> [RQ_B] *Through an interaction system, is it possible to trigger a triage system, with the older adult, to determine the need for intervention?*

> [RQ_C] *With this platform, is it possible to determine potential dangerous situations, reducing the time of perception and intervention?*

The current research work proposes the development of a platform focused on the caregiver and her /his needs that tackles the aforementioned needs and requirements, answering to the proposed questions. Using low-cost technology that already exists in the market, it is possible to increment the platform modularly, making it more complete, as well as standardize the information from the peripheral and feed it with the necessary data for its operation. With the collected information, it is possible to take illations about the daily routine and activity of the older adult, understanding, as well, significant alterations to this pattern. When so, and after determination of the real need, it allows the caregiver to, actively and immediately, interact and trigger support mechanisms and, so, act effectively.

The usage must be transparent and straightforward, with the platform being responsible for the encapsulation of all data’s collection and modeling work, to formalize useful information to the needs of the caregiver and the analysis. To the older adult, the implementation must have a pervasive behavior and, simultaneously, transparent in their everyday activity, being the interaction with it done with high usability methods.

1.4. Expected Results

The technology exists and is accessible and effective when used for a specific purpose but becomes complex and unmanageable as a complete solution.

The solution would pass through the idealization of a model of uniformity, of a large part of the technological types existing in small computing devices that, when connected, would create a flow of information, thus making this technology usable as a whole. To do so, there is the need to design an aggregating platform, which consumes information from these multiple devices or sensors, using the hardware-platform interface. Is expected that the data, when processed, will be translated into relevant information for the caregiver, managing to maintain constant monitoring of the routine of the older seniors under their care and their respective abnormal deviations from regular daily activity. The analyzed information would be useful in real-time and after triage if it would allow the caregiver to act when necessary and in context.

1.5. Research Methodology

One of the first occurrences of the term "*Urban Informatics*" can be found in Mark Hepworth's 1987 article "*The Information City*" (Hepworth, 1987), whose definition is understood by the study, conceptualization and implementation of experiments in different urban contexts, establishing notions, trends and considerations for space, technology and citizens, coming from ubiquitous technologies and real-time communication (Foth et al., 2011). Today, several research methodologies are emerging, focusing on the development and implementation of ubiquitous and pervasive technologies with a focus on emerging trends, such as, IoT and smart devices. One of the most relevant for the study in the field of *Urban Informatics* is the *Participatory Action Design Research* (PADR) (Figure 1), which combines *Action Design* methodologies (Sein et al., 2011) and *Design Science Research* (Bisandu, 2016). Both are used in information systems, aiming at the need to respond to the specificities of *Urban Informatics* concept, supporting computer research in the development of new technological means to solve contemporary issues or support daily life in urban environments (Bilandzic & Venable, 2011).

Action Research investigates a phenomenon through intervention in a problematic situation, distinguishing itself by working simultaneously to improve the problematic situation while investigating the phenomenon of interest. On the other hand, *Design Science Research* focuses on the development and performance of artifacts (such as algorithms, human-machine interfaces, methodologies and languages), with the explicit intention of improving their functional performance. It aims to enhance the approach of PADR (see Figure 1), not to directly concatenate both methodologies described, but to adopt the best of both, focusing on the problem of *Urban Informatics*.

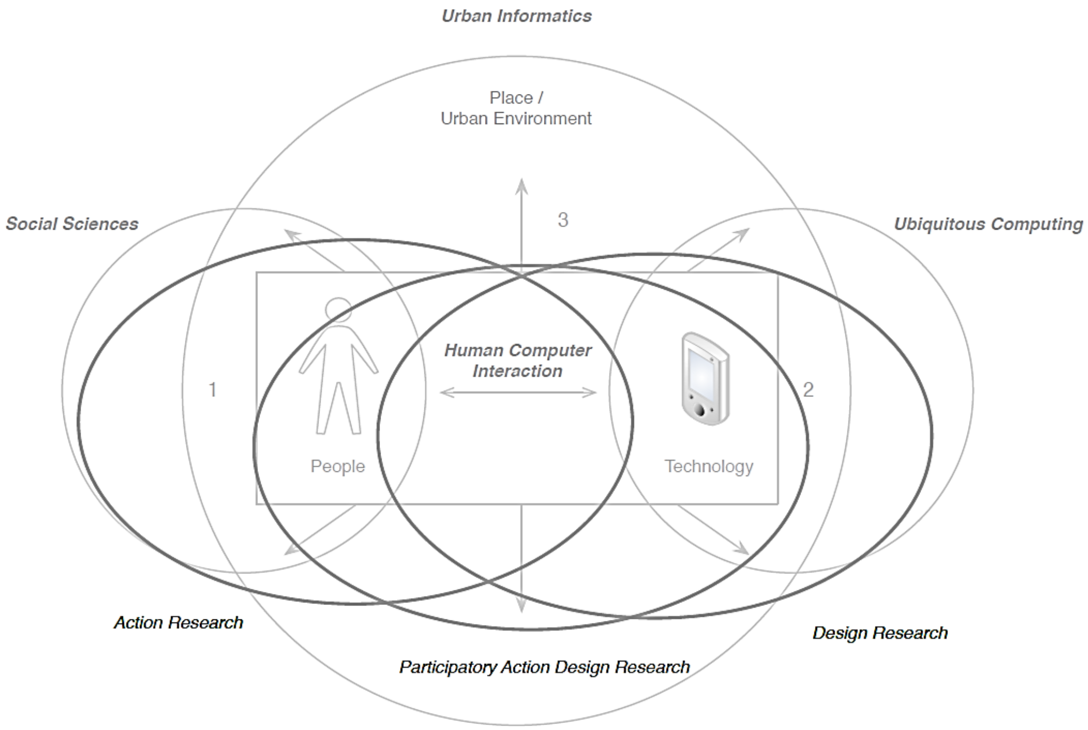

*Figure 1 - PADR incorporates technological innovation with methods to shape design according to the socio-cultural context [Source:*Bilandzic & Venable, 2011*]*

The PADR then consists of an iterative process of continuous improvement, which focuses on the participation of all stakeholders in the process, subdivided into five phases or activities: (1) Diagnosis and Problem Formulation, (2) Action Planning, (3) Action Taking: Design, (4) Impact Evaluation and (5) Reflection and Learning (see Figure 2).

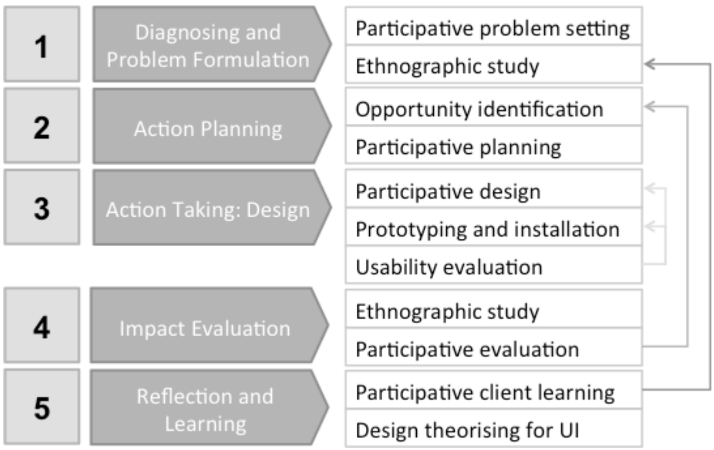

Figure 2 - Participatory Action Design Research - research method applied to Urban Informatics [Source: Bilandzic & Venable, 2011]

The use of this methodology makes sense in the scope of this dissertation, as it focuses on exploring emerging concepts and technologies, and it is necessary to validate if this technology fully enables the proposed implementation, and in parallel, it is crucial to validate if it meets the expectations and needs of both the caregiver and the older adult.

1.6. Main Contributions

The main contributions made by this work are the following:

ICAN(b)E - Support Platform - Conceptualization and implementation of a support platform that aims to respond to existing needs, in order to provide the caregiver with a set of tools to assist her/him in this same process. The platdorm can track and monitor the older adults' daily activities, actively transmitting information in real-time to caregivers for supervision and intervention. The platform also serves as an intermediary in the intervention, in a first triage and validation of the need for intervention, in case of identification of anomaly or possible potential risk.

ICAN(se)E - Tracking and Monitoring - Internal module of the ICAN(b)E system, which provides a set of tools for data analysis, using machine learning approaches to analyze and classify the data extracted from peripheral devices interconnected with the platform, in order to detect situations relevant to the analysis of the caregiver, facing the older adults.

1.6.1. Invited Talks

During this research work, the conceptualization of the platform was presented and discussed in the following contexts:

IN2SET - Aging and Well-being (February 2019) - talk regarding the initial proposal of the thesis, in front of a vast working group composed of several internal and external members, including researchers and professors from different areas of IPS, as well as representatives of municipalities (Almada, Montijo, Barreiro and Setúbal) and entities, which act in different areas that are interconnected toward the care of the older adults.

12th International Week - Making networks for the next 40 years (November 2019) - 12th International Week of the Polytechnic Institute of Setúbal with participation in plenary sessions and participation in an R&D round table, in a working group focused on the theme of aging. The platform was presented and discussed within a group of international participants.

1.6.2. Publications

During this research work, a small part of the results obtained were materialized on the full paper *“Yes, ICAN(b)E - Active Aging in Place supported by a Caregiver-centered Modular Low-Cost Platform”* (Capinha et al., 2020), which aimed to present the proposal of a low cost platform for active aging with focus on the caregiver, on the 6th International Workshop on Ambient Assisted Technologies for HealthCare (AATCare 2020), afliliated workshop of the 10th International

Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH 2020), with publication from Elsevier in the Procedia Computer Science journal.

1.7. Document structure

This document contains six more chapters, structured as follows:

- Chapter 2 (Background and Related Work) presents the concept of active aging and describes the main notions of the surrounding context and technology, where this research work is inserted.

- Chapter 3 (Proposed Solution) focuses on the conceptualization of a solution that aims to respond to the needs exposed in the current chapter, given the support of the caregiver's tasks, with the implementation of a platform for tracking and monitoring the older adult in their daily routine.

- Chapter 4 (ICAN(b)E - Support Platform) presents the implementation of the conceptualized solution, focusing on the technology and decisions inherent to it, reflecting its behavior and internal functioning.

- Chapter 5 (ICAN(se)E - Tracking and Monitoring) presents the study, conceptualization and implementation of the central module, which aims to meet the needs of data processing and machine learning of the platform developed, capable of making predictions from data consumed from smart devices integrated with the platform. Here are also presented the results obtained from the validation of the implementation of the platform carried out in situ.

- Chapter 6 (Conclusions and Future Work) summarizes the research work in the most relevant conclusions and presents the current state of research and future work.

2

Background and Related Work

This chapter presents the background and state of the art of the main topics related to this research work, which are indispensable to its study and understanding. The theme of active aging and the role of the informal caregiver is addressed, followed by the study areas and technical components necessary for the development of a platform. Also, a set of projects related to the study area is mentioned.

2.1.Aging

The definition of aging is characterized by changes at the biological, psychological, morphological, and functional levels, resulting from the passage of time. These transformations can be reflected at the level of intellectual, social interaction, activity, and behavior (Castro, 2007; Ferreira, 2005; Lima, 2002). The aging process is naturally associated with the progressive detriment of biological and functional capacities, which are not the result of accidents or disease (Ramos Esquivel et al., 2009; Ribeiro, 2007). This concept consists of a complex and dynamic process that occurs throughout life, from birth to death (Woltereck, 1959).

According to a study carried out by the National Statistics Institute, the estimates tend towards an older population (see Figure 3). It is estimated that a third of residents in Portugal in the year of 2050 will be older adults, which would place the country as the third one with the most aged population in the world, surpassed only by Japan and Spain (INE & FFMS, 2017). This reality is transversal to the other European countries, which face the challenge of a demographic revolution, with a decrease in the birth rate and progressive increase in longevity (Quaresma, 2008).

The older population is faced with a set of physical-motor, cognitive and social difficulties. In the latter, motivated by a group of social losses and rejections, the older adults tend to experience social isolation, aggravated by the retirement, consequent little occupation and, in some cases, reduced contact with family members and interaction with the community (Terezinha & Valentini, 2003).

Greater longevity is related to the improvement of a set of factors such as health, education, quality of employment, income and social protection (Ribeirinho, 2016). Increasingly equated is the adoption and practice of a set of measures that enhance active aging in society, in order to overcome the adversities arising from the natural aging process.

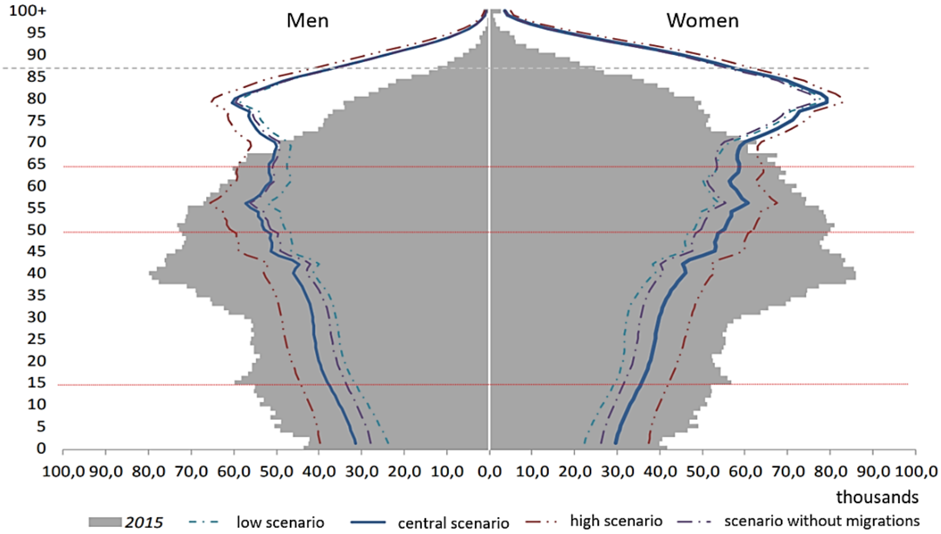

Figure 3 - Age pyramid, Portugal, 2015 (estimates) and 2055 (projections, by scenarios) [Source: Instituto Nacional de Estatística, 2017]

2.1.1. Active Aging

The term "active aging" was adopted by the World Health Organization (WHO) in the late 1990s. It was intended to convey a more inclusive message than the concept of "healthy aging" and to recognize factors beyond health care (Alexandre Kalache & Kiekbusch, 1997). Thus, it is defined as a protective policy based on three determining pillars: participation, health, and safety.

Active aging is an increasingly current challenge and, according to WHO guidelines, should be promoted intensively (OMS, 2015). In this context, active refers to the need to highlight all opportunities to continue the process of reintegrating the older adult into society, the economy, culture, making them feel useful and integrated, with a sense of belonging to society (WHO, 2012). The guidelines promote strategies for active and healthy aging, in order to provide opportunities for improvement “for people to live healthily and autonomously as long as possible until the end of their life” (A. Kalache & Gatti, 2003).

2.1.2. Informal Caregiver

A formal caregiver is one who, in addition to receiving training and education in providing care, is paid for performing their role, and is often affiliated with health care providers (The Johns Hopkins University, 2021).

Furthermore, an informal caregiver is anyone who provides care in a non-professional manner, and outside the exercise of her/his work activity, to a subject who needs care or has a disease, when s/he needs support (Pearlin et al., 1990). Although historically, there is a family relationship of a parent, a spouse, or another degree of kinship, this care can be provided by a friend, neighbor, or even by volunteering. However, this task adds several changes to their daily routine and adds difficulties, with the main ones being related to rest and leisure activities, family day-to-day, and economic management (Gemito, 2015).

Informal caregivers are often exposed to a high physical, mental, emotional, social, and even professional effort, causing an overload with a pejorative impact on their health, social life, and family context. This sometimes translates into negative psychological and/or physical consequences (Sousa, L., Figueiredo, D. e Cerqueira, 2004). The caregiver role has a lasting and daily character, which intensifies the impacts, in several domains, on the life of the caregiver. This is mainly due to the difficulty of combining this role with other roles and social activities (Gallagher-Thompson & Thompson, 1996).

Despite the arduous task and its conciliation with social and family life, with the integration of the older adults in society in an active way, consequently avoiding their institutionalization, caregivers adopt a very relevant role in this process, whether they have an active or passive position. If historically the care provided generally took place in the caregiver's home environment, today it will be possible to perform some monitoring remotely, with the help of existing technology.

2.2. Ambient Assisted Living

Ambient Assisted Living (AAL) concept can be defined as the application of Information and Communication Technologies (ICT) to older people's daily lives to remain active for a more extended period, inserted in society, and living independently.

With the increasing rate of population aging and consequent dependence on older people, this is a recognized need both socially and economically. Research on aging, age-related conditions and the means to support an aging population has thus become a priority for many governments around the world and the scientific community (Monekosso et al., 2012).

Research in this area has a broad thematic scope, with some of the most important being the recognition of human activity and daily routine, with the objectives of detecting and recognizing actions, activities, and situations within a delimited physical environment. Thus, it is seen as a subcategory of the area of study concerning the creation of intelligent environments, which combines the use of techniques, processes, and technologies used in the creation of smart spaces in order to allow older adults to live independently for as long as possible, without intrusive behavior.

This area follows a relatively new technological trend that has emerged in Europe since the beginning of the 21st century, to provide the environment with intelligent devices in a pervasive way to support unmonitored people. The emergence of the connected digital age plays a crucial role, especially in the emerging growth of IoT (*Internet of Things*) technologies. While technology cannot replace the comfort of human interaction, it can certainly assist in concrete everyday challenges.

Activity recognition can consist of the use of simple, non-intrusive and low-cost sensors. Can include motion sensors, location, drop monitoring, temperature, body vital signs, opening doors and windows, lighting, and many others (Wang et al., 2019). Most sensors in this category measure environmental parameters, deducing human activity by analyzing the values collected. This technology allows data collection without any resident intervention, thus increasing its operability and acceptance.

2.2.1.Smart Home

The concept of smart home, or home automation, appeared at the beginning of the 2000s, being directly connected to the domotics area, a subarea of robotics, defined as the integration of the automatic mechanisms of a space, simplifying the daily life of people, satisfying the needs of communication, comfort and security.

A smart home is a home that has highly advanced and automated systems to control and monitor any function of a house, such as lighting, temperature control, multimedia, security, window and door operations, air quality, or any other task of need or comfort performed by a resident of the house. With the increase in wireless computerization, remote-controlled devices are becoming intelligent just-in-time. Currently, it is possible to allocate a programmed chip to any inhabitant and have the systems adjusted as a person passes through an intelligent home. When connected to the Internet, home devices are an important component of the Internet of Things (IoT).

A home automation system usually connects control devices to a central hub or gateway. The user interface for system control can vary between wall-mounted terminals, tablet or desktop computers, a cell phone application, a web or voice interface, which can also be accessible off-site via the Internet.

Home automation has also been implemented in homes for the older adults and people with disabilities to maintain their independence and security, saving the costs and anxiety of moving to a health care facility (Cheek et al., 2005). In intelligent homes, this technology allows some independence to people with limitations, providing emergency assistance systems, security features, prevention and detection of falls and convulsions, automated timers, alerts, and allowing monitoring by family members through an Internet connection (Majumder et al., 2017). As a rule, these systems focus on the specific needs of their owners (Demiris & Hensel, 2008).

2.2.2. Internet of Things

The term "Internet of Things" (IoT) was coined by Kevin Ashton of MIT's Auto-ID center in 1999. It can be described as the network of physical objects ("things") that can incorporate sensors, software and other technologies for the purpose of connecting and exchanging data with other devices and systems, using the Internet. Its definition has evolved due to the convergence of multiple technologies, such as, real-time analysis, machine learning, wireless sensor networks, control systems, automation (including home and building automation), the technological evolution of everyday intelligent devices and embedded systems, all of which together make possible the implementation of IoT technology as it is known today.

In the consumer market, IoT technology is strongly related to products belonging to the "smart home" concept, including devices and appliances, such as, lighting fixtures, thermostats, home security systems, and cameras, among other household appliances, which support one or more common ecosystems, and can be controlled through devices associated with this ecosystem, such as smartphones and intelligent speakers, with different types of inputs and interfaces.

The vast array of applications for existing IoT devices (Rghioui et al., 2014) is often divided into different targets, such as private consumer, commercial use, industry, infrastructure, and military (Perera et al., 2015). In the context of intelligent homes, a fundamental application of IoT technologies is providing assistance to older adults, enabling remote monitoring of their activity and daily routine in their home, allowing a prompt intervention in case of need by caregivers or entities. Another important and fundamental aspect for their exponential growth is the low cost of some existing solutions in the market, as well as the scalability that these solutions allow.

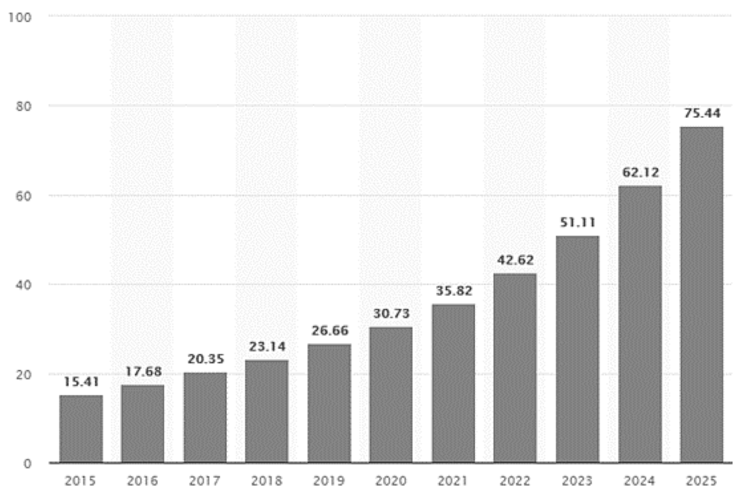

Figure 4 - Internet of Things (IoT) devices connected to the Internet worldwide from 2015 to 2025 (in billions) [Source: Statista Research Department, Nov 27, 2016]

The total number of devices installed, connected to the Internet of Things (IoT) should reach 75.44 billion worldwide by 2025 (see Figure 4), which represents an increase of five times in ten years. IoT, made possible by the already ubiquitous Internet technology, is the next big step in fulfilling the Internet's promise of making the world a connected place.

2.2.3. Ubiquitous Computing

Mark Weiser coined the term ubiquitous computing (UbiComp) in 1991, through her/his article "*The computer of the 21st century*", as a futuristic vision, in which humans and computers are perfectly interconnected, where technology is at the disposal of the human, dissipated in their daily lives and in an indistinguishable and omnipresent way (Weiser, 1991). UbiComp, also identified by *everyware*[3], is essentially defined as an emerging trend associated with incorporating microprocessors in everyday objects, fully connected, allowing them to send information, substantiating research areas such as mobile computing and pervasive computing. In this ideology, computational systems are part of the user's environment, capable of extracting user information. Is an embedded environment populated by sensors, computers, and applications. Each component can detect the remaining components and interact with each of them, thus building an intelligent context.

The research in this area is concerned with solving a set of identified problems, such as those referred to in the area of active aging and AAL. The creation of pervasive environments, where technology is omnipresent in the user's physical context, capable of collecting data and weaving links, without the user noticing, opens doors to the desired solutions. In this type of solution, one of the essential functionalities is the detection, monitoring, and characterization of the daily routine activity. This

[3] An imaginary state of technological development in which information processing has been integrated into almost every item of everyday life, from clothing to packaging or even building materials.

process is fundamental to allow the development of effective solutions to help the older adults to live independently in their homes, which is eased by the unprecedented progress of technology such as wearables, smartphones, smart bands, mobile devices, wireless communications, among many others (Blackman et al., 2016).

2.3.Bluetooth Low Energy Beacons

The term first emerged with Apple's launch of iBeacon technology in 2013. Beacon devices are small, battery-powered wireless radio transmitters that use bluetooth low energy (BLE) as the transmission protocol and emit small, typically static data packets at regular intervals that can be received by other BLE devices (Vlugt, 2013).

These devices optimize power consumption by staying asleep most of the time, waking up only to emit data at pre-defined intervals. These intervals can range from a few milliseconds to a few seconds and must be adjusted to their purpose. A shorter transmission interval increases the number of packets to be transmitted, improving the readings' accuracy, but at the expense of higher power consumption. Other properties, such as signal strength (Tx, from the term *Transmisson Power*) directly correlated with the range of the emitted signal, have a significant impact on the energy consumption/performance ratio and should, therefore, be adjusted to the scope of the implementation.

The beacons have, nowadays, a wide range of applications in the market and distinct sectors (see Figure 5). Their use ranges from integration in indoor location systems, engagement in events and cultural spaces, gamification experiences based on the participant's location, promotion of marketing and branding actions, Internet of Things (IoT) solutions and smart houses, industry 4.0 and manufacturing, among others.

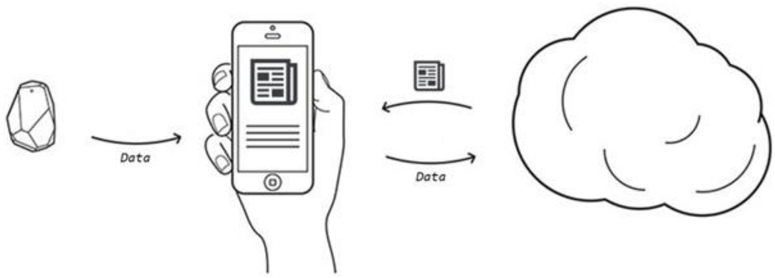

Figure 5 - Example of access to information from a beacon device via a mobile device

2.3.1.Beacon Protocols

Like any other technology, BLE Beacons work with a set of protocols. It is like a profile that tells how a beacon is transmitting the information. The Beacon protocols format the data field by dividing it into small segments containing information alluding to the beacon, such as signal strength, output power, etc (see Figure 6). This information is represented in hexadecimal values, and then it is treated by a device (receiver) responding to the same protocol. Both ends must know the definition of the transmission data if they want a successful transmission. Therefore, the type of broadcast data is defined by the type of protocol the beacon is using. The most popular beacon protocols are iBeacon and Eddystone.

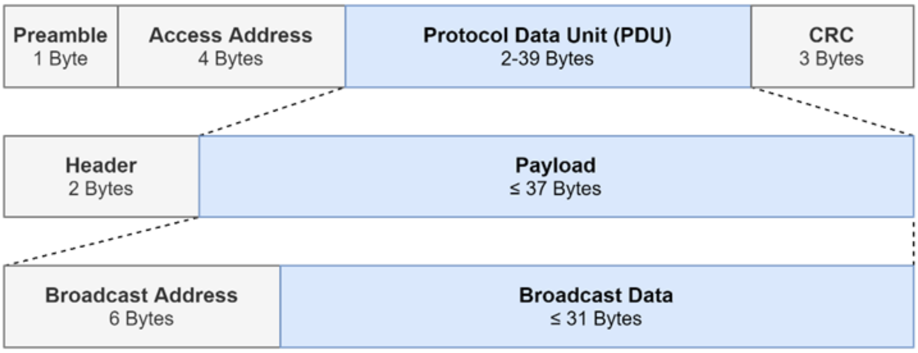

Figure 6 - Bluetooth low energy data package

iBeacon

iBeacon is a communication protocol developed by Apple in 2013, and it was the first beacon protocol on the market. Works with both iOS and Android from Google and is widely supported, simple and easy to implement and has a reliable performance on iOS. This system is typically used to estimate the distance between transmission and reception devices.

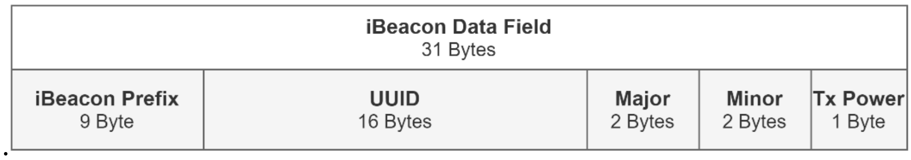

Figure 7 - iBeacon protocol data field

The iBeacon package contains a field called UUID used to identify a specific application related to the beacon (see Figure 7). This means that each application-related beacon will have the same identification. The Major and Minor values are mainly used to identify the beacons when deployed in small subgroups. In this case, the Major value is used to identify each subgroup, and the Minor value is used to identify specific beacons within the subgroup.

Eddystone

Eddystone is an *open-source*[4] beacon protocol developed by Google, designed to be "transparent". Can be detected by both Android and iOS devices. The Eddystone protocol is based on the lessons learned from working with industry partners on existing implementations, as well as with the general community that develops solutions with beacons (see Figure 8). Eddystone can have different types of payloads, depending on the intended purpose, such as:

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[4] Open Source is a development model that promotes free licensing for software design and development, assuring its creators credits and users the right to use, redistribute and adapt.

- **Eddystone-UID:** The unique ID (UID) is a unique static ID (similar to UUID, Majors and Minors) with two parts: Namespace and Instance.
- **Eddystone-URL: I**ncludes a compressed URL which, once analyzed and uncompressed, is directly usable by the client (Web Physics[5] concept).
- **Eddystone-TLM:** Beacon status data (telemetry) that are useful for the maintenance and diagnosis of the devices.
- **Eddystone-EID:** Allows the sending of variable encrypted identifiers, adding an additional layer of protection, avoiding the risk of being tracked by malicious third parties.

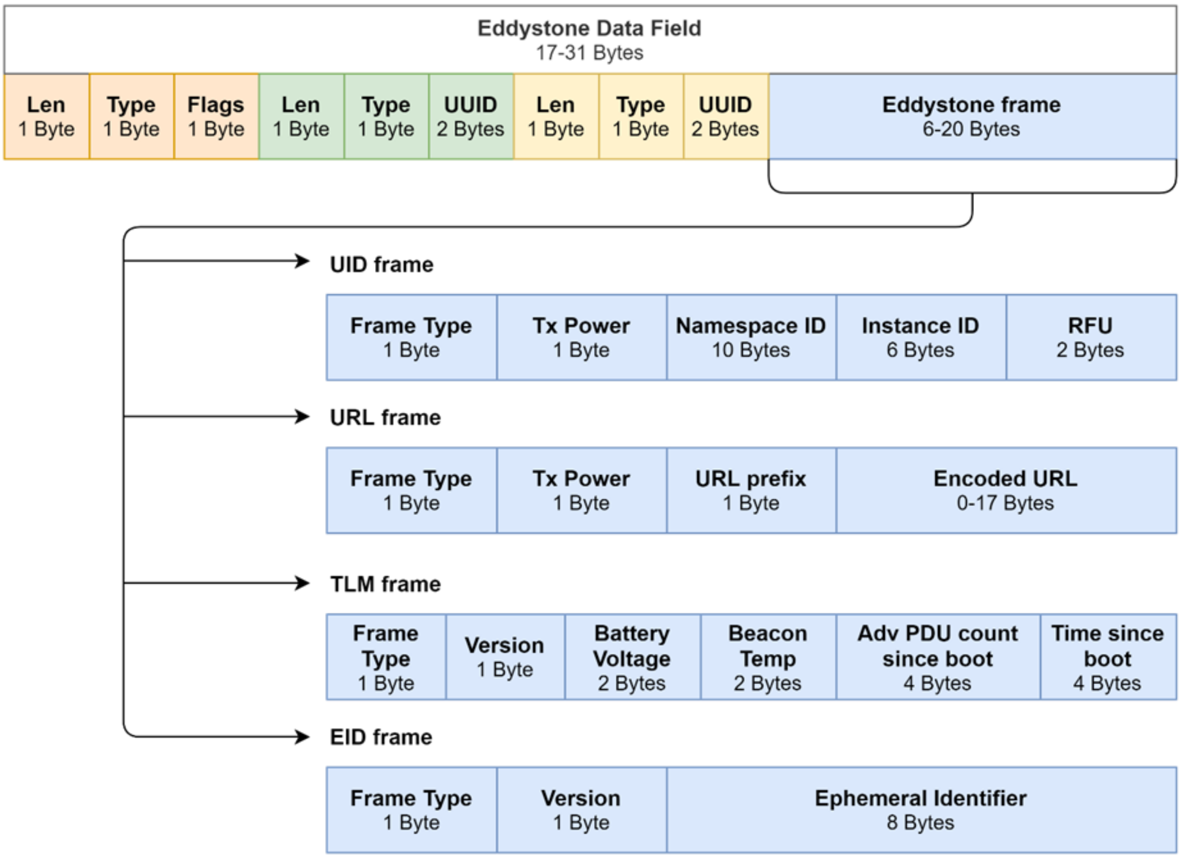

Figure 8 - Eddystone protocol data field

2.3.2.RSSI - Received Signal Strength Indication

Bluetooth LE can be used to measure distances between a given receiver and a beacon device. One way to do this is for the receiver to use the RSSI (Received Signal Strength Indication) parameter

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[5] Physical Web is an open approach to allow fast and continuous interactions with objects and physical locations. It allows obtaining a list of URLs being transmitted by objects in the physical environment around them.

value. This parameter represents the number, in dBm[6] units, produced by the receiver Bluetooth hardware that gives the wireless signal strength. The value of this parameter is negative as the more it tends to zero, the closer it is in relation to the transmitter. Is possible to subdivide different levels of proximity according to the parameter's value ranges. As a rule, this measurement is between -10 dBm (very close) and -90 dBm (very far).

However, the relationship between the RSSI value and the calculated distance is not linear, depending on several factors at the level of the hardware's specificities and the physical environment surrounding it. The introduction of "noise" to the obtained signal, of an electrical nature, physical blockage or reflection, is also a constant, contributing to a more significant margin of error.

Some beacon protocols, such as the iBeacon, contain transmission information regarding the measured power, which can be taken into consideration in case different beacons have different transmission power (Tx) and, consequently, different RSSI at the same distance. As a rule, the measured power presents a value for a distance of one meter from the transmitter.

2.3.3. Calculation of the Approximate Distance

One of the simplest and most common ways of measuring proximity to a beacon device is calculating the distance between receiver and emitter, through the RSSI (Al Qathrady & Helmy, 2017). This parametric model uses an equation to estimate the distance:

$$distance = 10^{\frac{RSSI - RSSI_1}{10n}} \tag{2.1}$$

$RSSI_1$ represents the average RSSI when at one meter away from the BLE beacon device, regardless of the Tx power emitted, often known as calibration power. The value "*n*" represents the exponent of the loss in the path, and this constant depends on environmental factors, and it is in the interval [2, 4]. It can be calculated using the following formula:

$$n = -\left(\frac{RSSI - RSSI_1}{10 \log_{10} d}\right) \tag{2.2}$$

The attenuation exponent should be calculated for each reference device and vary depending on the environment, i.e., the obstacles and interference affecting the signal. In an open environment (free space), the attenuation exponent value is two (Yu Gu & Ren, 2015).

[6] dBm stands for Decibel-milliwatt, a unit used to measure the radio frequency (RF) power level. dB (without the "m") measures the power of a signal according to its relation to another standard value, and the "m" in "dBm" indicates that it is compared for 1 mW of power.

The calculated distance is the approximate distance and not the exact distance, because the loss factor (environmental factors) would have to be zero to calculate the precise distance.

2.4.Real-Time Location Systems

Real-Time Location Systems (RTLS) are used to automatically identify and track objects or people's location in real-time, usually within a building or other designated area. Solutions can use different identification technologies to implement this type of systems. Regardless of the kind of technology used, there is a set of distinct approaches, with varying degrees of complexity and integrity, to the formula for calculating the positioning in the physical context. The most appropriate should be chosen for the context of the application.

2.4.1.Proximity-Based Position

Proximity-based positioning is a simple and crude positioning method that requires only one reference node in an agent's range to determine a position. An agent's position is determined by assuming that the agent is located at the reference node from which the strongest signal is received. This method is usually used for proximity services due to unreliable positioning accuracy (Y Gu et al., 2009). An example of the use of this method is the wireless car keys. These allow drivers who use the keys to unlock and start the car by being close to it. However, although with relative precision, this method works with correction when necessary to determine the closest emitter node. Thus, this technique allows determining concrete positions in an indoor physical space when well applied, allowing, for example, determining which room a user is located in.

2.4.2.Trilateration

Trilateration consists of using the RSSI received with geometric calculations to determine the position of an agent. To achieve this, three reference nodes of the agent's range are needed to determine a position (see Figure 9). Starts by measuring the signal strength of the reference node signals to determine a radius corresponding to the measured value. When calculating the point of intersection of the circles, the midpoint is determined and, subsequently, the position of the agent can be determined.

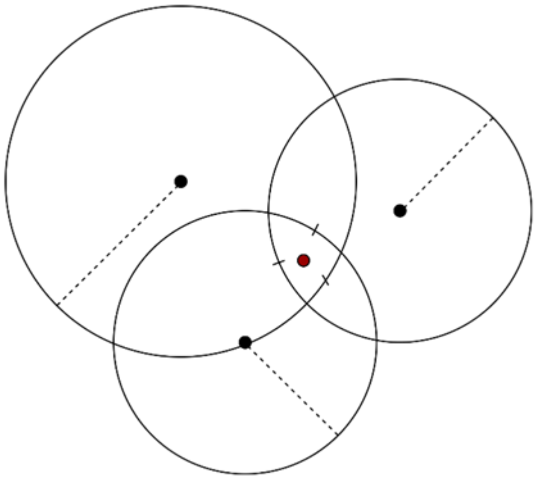

Figure 9 - Three-knot trilateration concept

2.4.3. Fingerprint

The fingerprint uses the RSSI values of a group of devices to create a signature (fingerprint) from a specific location, which is done by storing the values in a database over a period of time with the addresses of their corresponding devices. Once fingerprints are created from different locations, continuous scans are performed, and a fingerprint is always generated at runtime. The latter is then compared with each of the stored fingerprints in order to obtain the closest match (based on probabilistic models) representing the location of the user.

2.5. Natural User Interface

The term Natural User Interface (NUI), which has gained popularity in the field of Human-Computer Interaction (HCI) as well as in the consumer electronics industry in recent years, was first introduced by Steve Mann in 2001 (Mann, 2001), although in a different context from the one known today. In 2011, a group of experts encouraged a discussion to stimulate the exchange of knowledge on the subject, where they describe natural user interfaces as those that allow their users to interact with computer systems in the same way they interact with objects in the real world (Jain et al., 2011). They argue that these interfaces are based on combinations of inputs and outputs that are perceived as natural by users. This includes interfaces, such as gesture, body language, proximity, position, audio and visual inputs, eye direction, expression, smell, object location and touch. For an experience to be perceived as natural to the user, it must be multimodal, since this is a characteristic of real-world experiences. A multimodal experience is one that uses a combination of inputs and outputs where there is more than one input and/or more than one output.

Continuously, the evolution of modern devices is changing the way people interact with technology, and certainly facilitate the creation of more natural and intuitive interfaces, to be used by users (Goth, 2011). Some scientists even argue that NUI will become the dominant paradigm in interaction design (Krummelbein & Nuur, 2013).

The emerging technological evolutions have also allowed equipping daily electronic devices with technology that allows exploring other forms of interactions. An example is the increasingly common use of voice interaction mechanisms, which can offer adequate alternatives to the usual interaction modalities. Notably, in situations where other interaction techniques, such as using a mouse, keyboard, or touch, can be limiting or even forms of distraction from the task performed. A concrete application for this type of technology can be found in Ambient Assisted Living solutions, which aim to support older adults in their daily activities (Schlögl et al., 2014).

2.5.1. Voice Interaction

Voice User Interfaces (VUI), increasingly common and rapidly becoming ubiquitous (Stigall et al., 2019), enable human interaction with a computer system through speech, using speech recognition techniques and natural language processing, so that a given system can interpret spoken commands and typically produce a response and trigger actions. Since VUIs allow people to communicate through natural language, they become particularly attractive to users who may otherwise have difficulties using a graphical user interface (GUI) or touch-based methods (Vacher et al., 2015).

Smart speakers like Google Home and Amazon Echo are examples of new devices, increasingly common in the domestic context, which are part of users' daily lives and depend on hearing interfaces, on interacting with virtual assistants and other applications. Siri assistant is included in iPhones and Google Assistant in Android smartphones (Australian Communications and Media Autority, 2019), both by default. In the same way, Microsoft started to include its virtual assistant with voice Cortana in all Windows 10 devices in 2015, simultaneously to Apple, which began to equip all their computers with Siri. These systems are also often found in cars to facilitate driver interaction with the surrounding systems without losing focus on the driving task (Meng et al., 2020).

Advantages of using Voice Interaction in the Older Adults

Voice interaction platforms can add many benefits to specific groups of users, including those who may face challenges in using traditional physical input methods (Stigall et al., 2019), such as people with disabilities and the older adults, due essentially to the loss of fine motricity (Hoogendam et al., 2014).

This type of interaction can, from the beginning, constitute several benefits, because it overcomes the barrier of technological adaptation. Although little by little, and with a tendency to increase, the more recurrent use of new technologies by the older population starts to affect their technological literacy. A large part of this population still feels great difficulty in adapting to emerging technologies. Thus, voice interaction is a usage form specially designed for this purpose, which does not require prior learning because it simulates a fluid and similar interaction with the real world between humans.

2.5.2.Natural Process Language

Natural language processing (NPL) is a subarea of artificial intelligence, aiming at the computational understanding, analysis, manipulation, and generation of a natural language from an input, either textual or auditory (Figure 10). The history of NPL began in the 1950s when Alan Turing published the article "*Computing Machinery and Intelligence*" (Turing, 1950), which proposed what is now called the Turing[7] test as a criterion of intelligence.

As a technology, natural language processing has reached maturity in the last ten years, with Siri, Alexa, and Google voice search implementing NPL techniques to understand and respond to user requests. Sophisticated text mining applications have also been developed in diverse areas as medical research, risk management, customer service, insurance (fraud detection), and contextual advertising. Today's natural language processing systems can analyze a vast amount of data consistently and unbiased. They can understand concepts within complex contexts and decipher language ambiguities to extract key facts and relationships or provide summaries. Given the enormous amount of unstructured data produced daily, this form of automation has become essential for analyzing text-based data efficiently and promptly.

For several decades, extensive research has been conducted in the field of NPL with a focus on facilitating its use and increasing performance and effectiveness, which has led to the development of a vast number of different methods and techniques. Conventionally, the process can be divided into four primary steps, as shown in Figure 10.

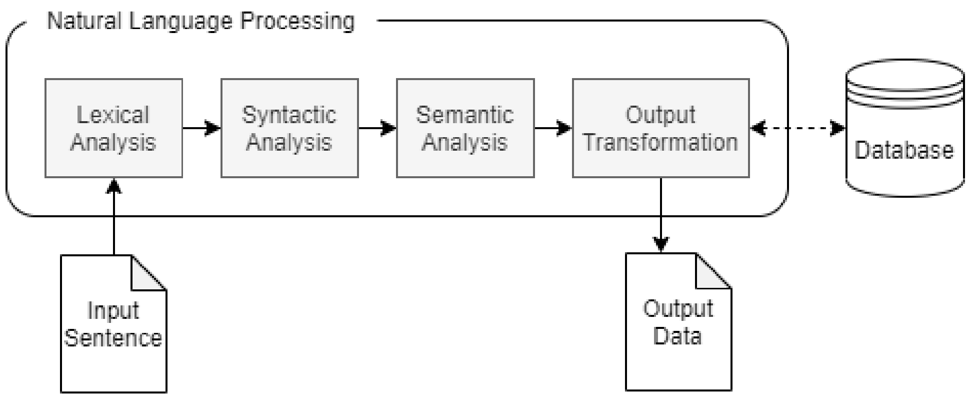

Figure 10 - Natural language processing

[7] The Turing Test tests the ability of a machine to exhibit intelligent behavior equivalent to, or indistinguishable from, a human being.

1. **Lexical Analysis**: This step analyzes sentences in natural language by dividing them into small items, each called a *token*. In addition, the *tokens* are identified, and some essential information will be used in the next step.
2. **Syntactic Analysis**: In this step, all *tokens* are analyzed with pre-defined sentence structure (Syntax) to check the validity and provide some information to be used in the meaning analysis process.
3. **Semantic Analysis**: The semantic analysis process interprets the meaning of a sentence through information analysis, which derives from the previous step with a semantic structure such as an ontology or a semantic web structure to provide some data representing the meaning of a sentence.
4. **Output Transformation Process**: This step transforms the results derived from Semantic Analysis into results that meet the objectives for the specific purpose, which allows computers and humans to work in cooperation.

2.5.3.Text Mining

Text Mining can be defined as part of a knowledge discovery process, in which it seeks to extract useful information from data sources by identifying and exploring patterns. Collections of text documents represent these data sources, and the patterns are found in the unstructured data of these documents. The discovery of these patterns can include sophisticated linguistic processing techniques, statistics, or even based on a selection of keywords. Thus, Text Mining is a process that seeks to turn unstructured text documents into usefully structured information, unlike Data Mining which aims to apply a set of different approaches and techniques in the search for patterns and relationships in data previously stored in a structured format.

Generally, this process involves applying a set of Machine Learning and Artificial Intelligence techniques and algorithms, intending to classify and assign meaning to textual sets. Starts by loading the Corpus, which in Text Mining is nothing more than the collection of documents used in the analysis and discovery of patterns, in an machine learning system, which will be analyzed to remove some linguistic, statistical, or other value from them.

There is a set of techniques, necessary for the transformation of the text in analysis, to facilitate the classification process. The pre-processing is a critical step in the process of Text Mining and information extraction, having as main objective to extract knowledge from unstructured data. In this phase, the characters, words, or set of identified words are pre-processed because, usually, in the text, there are particular formats, such as dates or numeric, as well as the most common words to occur in all documents, which hardly help the system. The pre-processing can be divided into several steps aimed at reducing the data to be extracted from documents, increasing its meaning (relevance), thus improving the efficiency and effectiveness of the classification system:

- Removal of *stopwords* to avoid confusion with terms that may be considered important, since *stopwords* are language-specific words that have no informational content for the classification process, such as pronouns, prepositions, conjunctions, etc. English words such as "the", "of", "and", "to" are irrelevant from the point of view of analysis since they are words that occur in all documents, several times.
- The *tokenization* technique is the process of dividing a text into words, phrases, symbols, or other significant elements, called *token* or *n-gram*, which correspond to the combinations of N-words "together" that can be created from a *text*. The objective of this technique is to explore the existing words in a text, creating a set of *tokens* that will serve as input at a later stage of the system. The *tokenization* process also involves a previous step, which is the removal of punctuation (for example, through the use of *Regular Expressions*). The main reason for using *tokenization* is to identify the keywords with the most significant value.
- Stemming is the name given to the word processing technique where all the words found are reduced to their radical (stem), i.e. to their root or base form, removing any suffixes from it. This process is quite essential since words whose base is the same usually have similar meanings or represent relatively close concepts so that words can be reduced to their radical (see Figure 11). One of the best known and widely used algorithms in this context is Porter Stemming (Porter, 1980).

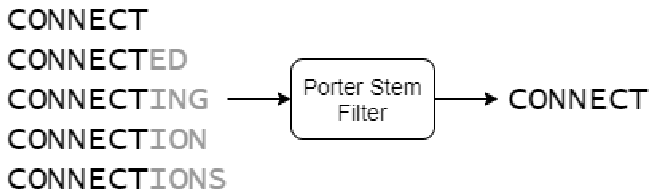

Figure 11 - Example of words that have a stem in common

- Another frequent step in the pre-processing is transforming all the existing terms in the text, in lowercase, to reduce the number of terms.

After the initial transformation, the terms are stored in a vector called *Bag of Words*, which stores, for each term, a set of characteristics, regardless of the order in which these terms appear in the original document. These characteristics are typically related to the frequency of a particular term in the document, or set of documents, and, consequently, the relevance of this term in the document:

- The concept of Term Frequency (TF) is simply the ratio of the term count present in a text to the total number of terms in the text. Thus, it can be generalized as follows:

$$TF = \frac{(Number\ of\ times\ the\ term\ T\ occurs\ in\ a\ document)}{(Number\ of\ terms\ in\ a\ document)} \tag{2.3}$$

- The Inverse Document Frequency (IDF) corresponds to a metric to determine how rare a term is among the various documents. The calculated value has the effect of highlighting words that are distinct (contain useful information) in a given document. Thus, the IDF of a rare term is high, while that of a frequent term is probably low. The IDF is calculated using the following formula:

$$IDF_{(t)} = \log(N/d_{(t)}) \tag{2.4}$$

  Where t represents the term, N the number of documents in the corpus, and d the number of documents where t occurs.

- The Term Frequency-Inverse Document Frequency (TF-IDF) is a statistic that aims to reflect how important a term is in a document, relative to the corpus. A high TF-IDF value is achieved through a high frequency of the term in a document and a low frequency of the same term throughout the document collection. The TF-IDF is calculated using the following formula:

$$TF - IDF_{(t)} = TF_{(t)} * IDF_{(t)} \tag{2.5}$$

  Where t represents the term, TF the frequency of the term in the document and IDF the inverse frequency of the document for that term.

2.6.Machine Learning

Machine learning (ML), a term first coined by Arthur Samuel in 1959 (Samuel, 1959), and seen as a subset of artificial intelligence, is the area of knowledge that deals with research and development of algorithms that provide systems with the ability to learn and improve automatically with experience without being explicitly programmed. ML focuses on developing computer programs that can access data and use them to learn for themselves, extract knowledge, recognise patterns, and produce links.

The types of ML algorithms differ in their approach, in the type of input and output data, and also in the type of task or problem they are intended to solve. These algorithms aim at solving problems using binary classification techniques (sentiment analysis, spam detection, credit card fraud detection, prediction of heart disease), multiclass classification (problem classification, object classification, product recommendation), regression (price forecast, sales forecast, trend forecast), anomaly detection (peak sales detection, credit card fraud detection, customer segmentation), ranking (search engine ranking), computer vision (image classification prediction, object detection). Generically, these algorithms can be grouped as follows:

- **Supervised ML algorithms** can apply what has been learned in the past to new data, using classified examples to predict future events. The learning algorithm produces an inferred function to predict output values from the analysis of a known data set.

- **Unsupervised ML algorithms** are used when the information used in training is neither classified nor identified. Unsupervised learning studies how systems can infer a function to describe a hidden structure from un-labeled data.
- **Semi-supervised algorithms** lie somewhere between supervised and unsupervised learning, as they use classified and unsorted data for training. Typically, a small amount of classified and a large amount of unclassified data. Typically, semi-supervised learning is chosen when the labeled data acquired requires qualified resources relevant to the training/learning process.
- **Learning reinforcement algorithms** are the formation of ML models for decision making. The agent learns to achieve a goal in an uncertain and potentially complex environment. It differs from supervised learning in that it does not require classified input/output pairs to be presented (Kaelbling et al., 1996). A computer program interacts with a dynamic environment in which it must accomplish a certain goal (such as driving a vehicle or playing a game against an opponent). As it navigates through its problem space, the program is provided with feedback that is analogous to rewards, which it tries to maximize.

Despite the specifics of each ML project, it conventionally follows a generic workflow:

1. **Data collection -** The data set can be collected from various sources such as a file, database, sensor and many other similar sources, but the collected data cannot be used directly to perform the analysis process since there may be a lot of missing data, extremely large values, unorganized text data or disturbances. Therefore, to solve this problem, a data preparation process is performed.
2. **Data pre-processing -** The raw data, when collected, needs to go through an important complex process of cleaning and transformation, in order to standardize and obtain data capable of being consumed by the system.
3. **Investigation of the best model -** Is necessary to determine which model should be applied, given the type of data being analyzed and its scope. The main objective is to form the model with the best possible performance, using the pre-processed data, applying specific algorithms that allow obtaining the most reliable classification or determination.
4. **Training and testing the model -** For the formation of a model, the data set is typically divided into training data, validation data and test data. The classifier is trained using training data, tunes the parameters using the validation set and then tests the performance of the classifier using the test data.
5. **Evaluation -** Evaluation of models is an integral part of the process of its development. Helps find the best model representing data and predicting the performance that the selected model will have in the future. To improve the model, the model's hyper parameters can be refined and try to improve the accuracy and look at the confusion matrix to try to increase the number of true positives and true negatives. The evaluation should be done by the typology of the

model, for example, for the classification task, the model is evaluated by measuring how well a predicted category corresponds to the real category. And for the grouping, the evaluation is based on how close the grouped items are to each other and how much separation exists between the clusters.

2.6.1.Deep learning

Deep Learning (also known as structured deep learning) is part of a vast family of Machine Learning methods based on artificial neural networks, using supervised, semi-supervised or unsupervised learning (Bengio et al., 2013; LeCun et al., 2015; Schmidhuber, 2015) and it is a class of algorithms that uses multiple layers to progressively extract characteristics from raw data (Deng & Yu, 2014) (see Figure 12). Has revolutionized, with its application, areas such as computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, pharmaceutical industry, image processing, auditing and artificial intelligence applied to games, where it has produced results comparable and, in some cases, superior to the performance of human experts (Ciregan et al., 2012; Zhang et al., 2020)

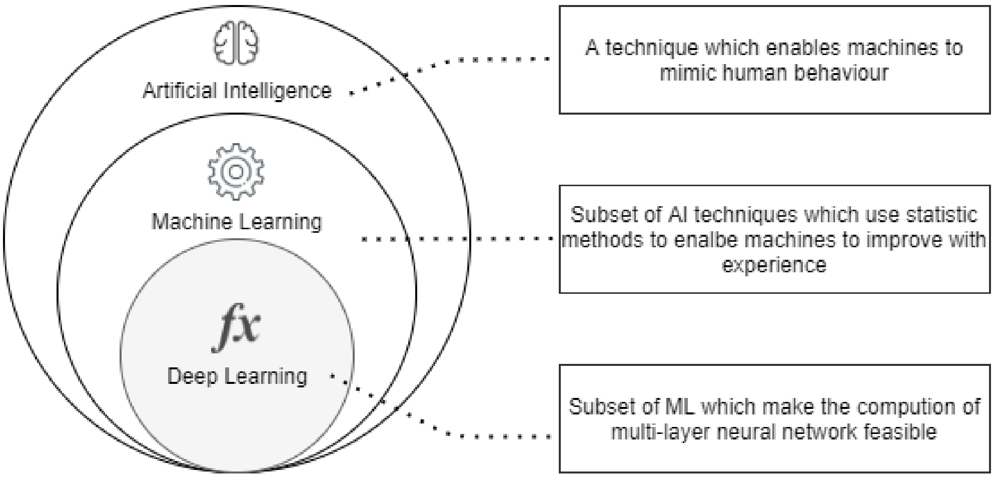

Figure 12 - Relationship between Artificial Intelligence, Machine Learning and Deep Learning

2.6.2.Neural Networks

Artificial Neural Networks (ANN) is generally a network or circuit of biologically inspired neurons (which are made of artificial nature), and therefore composed of artificial neurons or nodes, configured to perform a specific set of tasks (Hopfield, 1982).

The ANN can be used in several areas and applied to solve problems that fall into different categories such as function approximation, regression analysis, including forecasting and time series modeling, in areas of classification, such as pattern and sequence recognition, anomaly detection and sequential decision making, or in data processing, including filtering and clustering. Application areas include non-linear system identification (Domains et al., 2013), being common in control (vehicle control, process control), game and decision making, pattern recognition (radar systems, facial identification, object recognition or fingerprint), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications, data mining.

Typically, ANNs can be seen as weighted directed graphs, where the nodes are formed by the artificial neurons and the connection between the outputs of the neurons and the inputs of the neurons can be represented by the weighted directed edges. The ANN receives the input signal from the outside world in the form of a pattern and image in the form of a vector. These inputs are then mathematically designated by the x(n) notations for each n number of inputs (Figure 13). Each input is then multiplied by its corresponding weights (these weights are the details used by artificial neural networks to solve a given problem). In general terms, these weights typically represent the strength of the interconnection between neurons within the artificial neural network. All weighted inputs are added together within the computer unit (plus an artificial neuron). If the weighted sum equals zero, a bias is added to make the output different from zero or to scale to the system response. The bias has the weight and the input is always equal to one. Here, the sum of the weighted inputs can be in the range from 0 to positive infinity. A particular limit value is compared in order to keep the response within the desired value limits,. And then the sum of the weighted inputs is passed through the activation function. In general, the activation function is the set of transfer functions used to obtain the desired output from it. There are several variants of the activation function, but mainly sets of linear or non-linear functions.

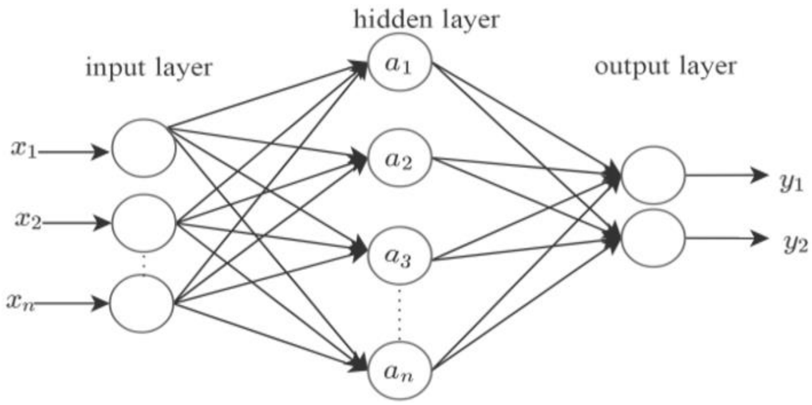

Figure 13 - Example of a neuronal network, represented in graph form

Nowadays, there are many types of neural networks in Deep Learning that are used for different purposes. Therefore, it is necessary to adapt the network to be used, through the intended purpose. The functions used in the nodes are also defined according to the scope.

2.7.Web Services and Cloud Computing

Web service is a solution used in system integration and communication between different applications. With this technology, it is possible that new applications developed can interact with those that already exist and that systems developed on different platforms are compatible. Web services are components that allow applications to send and receive data in a standard format. Each application can have its own "language", which is translated into a universal language, known throughout the integrated environment. It makes the resources of the software application available over the network in a standardized way, accessible by different systems, even if developed for different scopes, with different technologies or programming languages.

2.7.1. API REST

Representational State Transfer (REST) is a style of software architecture that defines a set of standards and best practices used to create Web Services. The term was first coined in 2000 by Roy Fielding in her/his PhD thesis (Fielding, 2000), later developed in W3C Technical Architecture Group. A Web Service compliant with the REST architecture is from now on referred to as RESTful Web Service.

Its architecture is based on the information exchange between clients and servers (Figure 14). The process is triggered by a client request, to which the server processes the appropriate response, being based on providing access to resources. A resource is the main abstraction of information, usually representing a document that captures the current or intended state of a given resource. Any information that can be named may be a resource: a document or image, a temporal service, a collection of other resources, a non-virtual object (for example, a person) and so on. REST uses a resource identifier to identify the specific resource involved in an interaction between components.

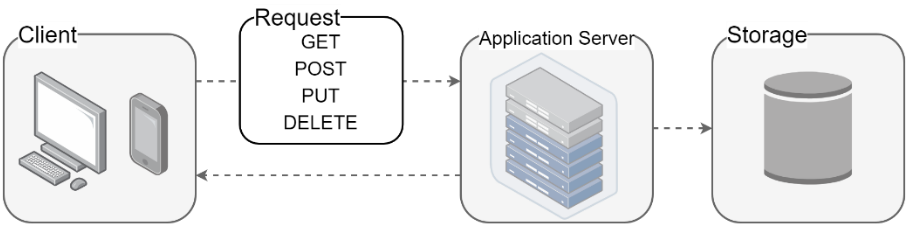

Figure 14 - client-server REST architecture

Using a client-server architecture, by separating the user interface's responsibilities from the responsibility of data persistence, the portability of the user interface on various platforms is improved and, consequently, the scalability, simplifying the server's components and resources. Although it does not use a strongly typified language, it follows solid guiding principles, described as follows.

Stateless - Each client request to the server must contain all information necessary to understand the request and cannot take advantage of any context stored on the server. The session status is maintained entirely on the client.

Cacheable - Cacheable restrictions require that data responding to a request be implicitly or explicitly labeled as cacheable or not. If a response is cacheable, the client cache has the right to reuse this response data for equivalent subsequent requests, allowing some performance gains.

Uniform interface - By applying the general principle of software engineering to the component interface, the overall system architecture is simplified and the visibility of interactions is improved. Several architectural constraints are required to guide component behavior in order to achieve a uniform interface. REST is defined by four interface constraints:

- **Resource Identification -** Each resource must have a Universal Resource Identifier (URI);
- **Resource representation -** Resources are manipulated from their representations, which can be in several formats, such as XML, JSON, TEXT, etc. An important detail is that a REST application does not effectively transmit the resource, but always a representation of it, in a pre-agreed format between the client and the server;
- **Self-descriptive messages -** Requests and responses must contain meta-data indicating how the transmitted content should be handled (headers for format, authentication, etc.);
- **Use of hypermedia for application status -** This prerequisite is the least met by self-titled RESTful applications: Resource representations obtained in a REST application must have hyperlinks that allow the client to navigate the resources. That is, unlike architectures based on RPC (Remote Procedure Call), the client must not previously know the URIs for the application resources (only the root of the service), and the server must provide links that allow the discovery of the resources by the client; there is no service contract, and there is no guarantee that a resource in a given URI may be available in the future;

System in layers - The application must be built in layers, and a layer can only see the layer immediately below. The main objective of this prerequisite is to ensure that applications are scalable;

Run code on demand - The client must be able to run scripts stored on the server in order to extend the client's functionality. An example of this is the ability of HTTP browsers to run JavaScripts, which is the only optional prerequisite for REST architectures.

In those considered RESTful Web Services, information is interpreted as resources and each one is linked to a global identifier (URI). Clients and servers communicate through a standardized protocol (HTTP) and exchange representations of these resources. Clients must have the resource identifiers and know the semantics of each HTTP method in order to manipulate them. Besides, there is no need to know the internal implementation of services or system configuration, such as caches, proxies, firewalls, tunnels or others between the client and the server that hosts the resources. However, clients should be able to interpret the returned data format, which is usually a JSON or XML document.

RESTful service methods

Typically REST uses HTTP methods to describe operations on resources. Similarly, there is a parallelism between HTTP verbs and CRUD (Create, Retrieve, Update, Delete) operations:

- GET: Used to read information about a resource. Can be used to list all the members of a collection or to get specific information concerning a single member of a collection;
- POST: Used for the creation of a new resource, it receives in the body the specifications of its attributes;
- PUT: Used to update information about a resource, usually identified through its identifier, receives in the body the values of the parameters to update;
- DELETE: Used to delete a resource or set of resources.

Good implementation practices

As RESTful services are among the most commonly used nowadays, it is essential to adopt good practices in their implementation to ensure the good functioning of this architecture.

- **Use of nouns instead of verbs** – Verbs should not be used in paths (URI) since the HTTP request method already has the verb. Therefore, it should be used unambiguous nouns of the entities intended to be manipulated, in the paths that refer to them.
- **Collections identified with plural nouns -** Plural nouns should be used whenever it is intended to refer to more than one object of the same type, which makes an analogy to the nomenclature used for data storage in the respective tables.
- **Order chained based on the hierarchy -** Paths suggesting resources with a defined hierarchy should respect this same hierarchy. That is, starting with the identification of the parent resource, proceeded by the respective children, like the hierarchy followed in the data source.
- **Error Handling -** A convention for error handling must be followed. If the API is based on the HTTP protocol, it should follow its error hierarchy and allow users who take advantage of this service to deal with management with which they are familiar.
- **Allow filtering, sorting, and paging -** Considering the vast amount of information stored, it is necessary to create mechanisms to deal with it, as well as ensure the sustainability of the

system. Filtering and paging increase performance by reducing the massive use of server resources. The more data the database accumulates, the more critical those resources become.

- **Maintain good security practices -** Most client-server communications should be private, since private information is usually sent and received. Therefore, the use of SSL / TLS for security should be constant.
- **Cached data to improve performance** – Cache can be used to return data from local memory instead of querying the database every time it is intended to retrieve some data already requested by users. The advantage is that users can obtain data faster and with less effort from the server. However, the data may be out of date. It, therefore, needs detailed analysis and good management of its implementation.
- **Versioning -** Different versions of the API should be identified when making profound changes in its behavior. Follows the conventions of software versioning.

2.7.2. Cloud Computing

Cloud computing is a model that allows ubiquitous, convenient, on-demand access to a shared network of configurable computing resources, such as networks, servers, storage, applications and services, which can be quickly provisioned and released with minimal management effort or interaction with the service provider. For enterprises, cloud computing means increased collaboration and productivity, as well as significant cost reductions. Often provides better data protection, better availability, and greater access to leading-edge technologies with far less investment in the infrastructure and manpower required to make them available, which is one of the biggest causes for the exponential growth of adoption and migration of services to the cloud (Attaran, 2017). In the future, more enterprises are expected to abandon proprietary infrastructure at the expense of more advanced and updated cloud architecture as the computer technology develops.

In general, and according to the National Institute of Standards and Technology (NIST), five essential characteristics define cloud computing (Kristiani et al., 2019), which are the following:

- **On-demand self-service -** Can be used whenever necessary and the payment can be made per use. Essentially, the cloud is a form of "utilitarian" computing. An account is created when choosing the provider, and the services will be available at any time.
- **Wide network access -** Should be possible to access, using any device with an Internet connection, wherever you are, the data in the cloud through web browsers.
- **Resource pooling -** Multiple hosts can share the same space, and resources can be assigned, reassigned, and distributed as needed.
- **Fast elasticity -** Cloud resources can increase and decrease as much as possible without affecting any of your users or their information. For example, if your business is experiencing peaks in traffic, the cloud can expand to accommodate all new requests.
- **Service measurement -** Cloud systems automatically control and optimize resource utilization. Thus, it enables measurement over a set of variables such as storage, processing, bandwidth, and active user accounts. Many cloud service providers use a pay-as-you-go model to ensure their customers are getting what they pay for.

Cloud implementation models indicate how cloud services are made available to users. The four most common implementation models associated with cloud computing are the following (Winkler, 2011):

- **Private Cloud –**Is provided for exclusive use by a single organization, comprising multiple consumers. May be proprietary, managed, and operated by the organization, a third party, or some combination of both, and may exist inside or outside the facility.
- **Community Cloud** – Provided for exclusive use by a community of consumers from organizations with common concerns. May be owned, managed and operated by one or more community organizations, a third party, or some combination of both, and may exist on or off facilities.
- **Public Cloud** – Provided for open use by the general public. May be owned, managed and operated by a business, academic or governmental organization, or any combination of the above. Exists on the facilities of the cloud provider.
- **Hybrid Cloud-** Composition of two or more distinct clouds (private, community or public) that remain unique entities, but are linked by standardized or proprietary technology that enables data and application portability.

Regarding the existing services, they are quite varied and can be grouped into primary groups, the most common being *Infrastructure as a Service* (IaaS), *Platform as a Service* (PaaS), *Software as a Service* (SaaS) and *Backend as a Service* (BaaS).

2.8.Existing Solutions

Globally, the global trend towards demographic aging makes Ambient Assisted Living a research focus. A valid AAL solution should offer a set of functionalities, including health monitoring, fall detection, communication and social inclusion, connectivity, voice interfaces, exercise monitoring, physiotherapeutic support, home monitoring, and robotic support platform. In addition to these functional features, performance, safety, resource utilization, and reliability are also equally important to ensure a solution's success (Kunnappilly et al., 2017). Next, some of the commercial solutions that stand out in the market will be analyzed.

2.8.1. AAL Programme

AAL is a European funding programme aimed at creating a better quality of life for older people and enhancing industrial opportunities in the field of technology and innovation for healthy aging. The funded projects usually address several key areas, including chronic condition management, social inclusion, access to online services, mobility, management of daily activities and support from informal carers (The Active Assisted Living Programme, 2015).

Favors the objectives of promoting innovative ICT-based services and systems for better aging at home, in the community and at work. Also aims to create a critical mass of research, development and innovation at the European Union (EU) level regarding technologies and services for this purpose. This programme is co-financed by the European Commission (through Horizon 2020) and 17 other countries until 2020, with a budget of approximately 700 million euros.

2.8.2. Similar projects

The current section identifies some projects with similarity to the proposal presented, highlighting their added value and areas of expertise.

CarePredict (CarePredict, 2020) is a project that arose in 2013 and focused on identifying standards in the daily lives of the older adults to predict declines in their health and allow early intervention by the caregiver. Combines wearable technology (bracelet used by the older adults), inner location (beacons), with machine learning algorithm for predictive analysis, thus managing to take illations about critical situations and changes in routine, alerting the caregiver. Also allows the older adult to ask for help, through a button located on the bracelet, as well as allowing voice communication with the caregiver, from this device. Also has algorithms for detecting falls, making this a complete solution in terms of monitoring.

Another interesting case is **SANITAG** (SANITAG, 2020), which is a company that provides indoor positioning systems optimized for the health sector. Has developed a solution using UWB[8] RFID[9] technology to locate, protect and monitor older adults with the communication of critical situations to the responsible caregivers. To do so, using wearable technology determines the position of the older adult in the physical space, as well as potential risk situations such as falls and prolonged inactivation. Also allows the generation of monitoring reports for analysis by the caregiver.

DOMO (DOMO, 2020) is a system whose objective is to sustain the independence of the older adult in their own home, with safety and quality of life. The platform certifies that the older adult can establish a request for help with the central at any time of the day in case of needing support. Has wearable equipment, which allows the detection of fall situations, triggering an automatic alert. This system can be complemented with other modules, such as biometric data collection, producing statistical reports on their clinical and motor status. Environmental sensors scattered around the house can perform the recognition of some daily activities. Also allows, with the use of specific hardware, monitoring and follow-up outside your home.

A case of an European project with AAL Programme funding is **2PCS (Personal Protection and Caring System)**, which is coordinated by the University of Innsbruck (Austria). Consists of a platform designed for professional caregivers, with which they can know the location of the older adult in a delimited space, using a wearable bracelet worn by them. Also allows the older adult to request for help through a button on the bracelet (2PC, 2020).

CARU (CARU, 2020) is a system focused on the use of voice interaction to establish direct communication with a caregiver. In case of need, the older adult can trigger a request for help, in this case through a voice command, followed by the notification of the caregiver. Also allows the recording and exchange of voice messages with the caregiver. The team of CARU is currently working on expanding the functionalities of this system with intelligent detection of critical situations and deviations in the daily activity routine.

Finally, **LIFEPOD** (LIFEPOD, 2020) is another solution that centralizes its functionalities in the hardware of voice interaction. Allows a caregiver to parametrize questions and routines with specific periodicity and moments to confirm their implementation by the older adult. This feedback is obtained by voice interaction with the older adult, and the caregiver has access to it through an online portal or

[8] Ultra-wide-band, also known by the technical name developed by IEEE 802.15.3. The UWB is used to reference any radio technology that uses a bandwidth greater than 500 MHZ or more than 25% of the center frequency, according to the US Federal Communications Commission (FCC).

[9] Radio-Frequency IDentification, is a method of automatic identification through radio signals, retrieving and storing data remotely through devices called RFID tags.

text message. Also allows the older adult to make requests for help, as well as integrates actions by voice with the other intelligent devices in their home.

Of all the solutions presented, CarePredict, SANITAG and DOMO projects stand out. These three solutions are among the most complete on the market, and all of them act in a pervasive way, with the capacity to detect daily activities and indoor location, in order to detect potentially critical situations, thus triggering the necessary support mechanisms, along with the solution proposed in this work. However, the CarePredict platform stands out for its similarity with our work in terms of monitoring and recognizing daily routines, promoting interaction and predicting potential dangers through predictive analysis of the patterns of detected activities.

Through direct contact with the companies supplying the detailed solutions, a cost estimate was made for the instantiation of each one of them, according to the information provided in Table 1. The estimated cost is the initial cost with the acquisition of necessary hardware plus installation, with a subscription (when applied) for one year, which can be renewed, with added values.

Table 1 - Comparative table of systems similar to the proposed solution

	Daily routine				Social	Hazard detection			Main aspects	Technology						Other	
Platform	Help with daily routine	Monitoring the daily routine	Recognition of activities	Recognition of indoor location	Help in promoting communication	Allows requests for help	Detects critical situations	Automatic alert to caregiver when critical situations are detected	Main aspects	Pervasive	Technologies	Sensors	Physical devices (interaction)	Monitoring system	Installation (hardware)	Country of origin	Estimated cost
CarePredict	×	✓	✓	✓	✓	Button	Inactivation and safe zone exit	✓	• Prediction of decline • Fall detection	✓	BLE	• Environmental • Body	• Bracelet	• Software • Mobile application	• RTLS system installation • Door locking system	USA	≃ 1100€
SANITAG	×	×	×	✓	×	Button	Fall and inactivation	✓	• Location monitoring • Fall detection	✓	UWB RFID	• Environmental	• Bracelet	• Software • Mobile application	• RTLS system installation	Turkey	n/a
DOMO	×	×	✓	×	×	Button	Fall and inactivation	✓	• Clinical monitoring and motor activity • Outdoor monitoring • Fall detection	✓	GSM / GPS	• Environmental • Body	• Bracelet	• Mobile application	• Motion sensors, doors, pressure and buttons	Switzerland	≃ 1300€
2PCS	×	×	×	✓	×	Button	×	✓	• Issue of aid applications	×	RFID	• Environmental	• Bracelet	• Software	• Needs placement of receiver antenna	Austria	n/a
CARU	×	×	×	×	✓	Voice	×	×	• Enhances communication	×	GSM	• None	• Voice interaction device	• Mobile application	×	Germany	≃ 950€
LIFEPOD	✓	✓	×	×	✓	Voice	×	×	• Validation of daily routine	×	WIFI	• None	• Voice interaction device	• Software	×	USA	≃ 500€
ICAN(b)E	×	✓	✓	✓	✓	**Voice**	**Inactivation and changes to routine**	✓	• **Detection of critical variances in daily routine** • **Triage mechanism**	✓	**BLE**	• **Environmental**	• **Bracelet** • **Voice interaction device**	• **Software** • **Mobile application**	• **Environmental Sensors** • **Beacons BLE** • **Receiving Gateways**	**Portugal**	**< 300€**

2.9.Discussion

The proposed solution is based on a totally pervasive system of low cost, with IoT technology that is already validated and existing in the market, discarding any need for intervention of the monitored subject, so that it operates autonomously. Thus, it is potentiated by the obtainment of results and its acceptance by the older adult.

The proposed model intends to support the caregiver in her/his task (which differs according to the necessities of the older adult in his/her care), with the use of complete monitoring, focusing on the routine of the older adult. Collects, analyses and determines information, such as their physical context in real-time and developed activities. This information is fundamental to determine patterns in their daily routine. Once determined, it serves as a comparative basis for momentary analysis, in order to perceive potentially critical deviations to this same known pattern. These deviations, when significant, may represent critical situations that need support or intervention. It is up to the platform to trigger the necessary mechanisms to interpret the intervention's severity or necessity. Metrics and patterns are continuously readjusted to enhance the analysis' assertiveness, using continuous learning mechanisms.

This solution also contemplates an intermediate triaging mechanism, which acts together with the older adult, with natural interaction mechanisms, after the detection of a potentially critical situation, managing to maximize the veracity of the analyses, through the elimination of false positives, thus reducing the need for intervention by the caregiver.

As previously analyzed, there are some solutions on the market that focus on aspects of maintaining the autonomy and independence of the older adults in their homes. To this end, they develop mechanisms for monitoring and predicting potentially critical situations. There are, however, numerous factors that raise the problem of ensuring the safety of the older adults or the effectiveness of action in the face of a problem. Thus, several of the analyzed platforms have performed quite significant work in terms of analyzing a small number of specific problems, with few being able to do so in a more comprehensive way.

Another problem associated with the inevitable physical and cognitive loss of the older adults's abilities is the fact that some solutions are supported by their interaction and the use of additional devices, which may lead, when incorrectly used or with an inadequate periodicity, to a failure in the correct functioning of the solution.

Inevitably, monitoring and location systems in real-time are related to the instantiation of emerging technology, which, although increasingly optimized in terms of efficiency and costs, still brings additional charges to implement complete solutions. Additionally, combining physical instantiation with software results in solutions with a very significant price, becoming inaccessible for a large portion of the older adults population.

Once the critical points are identified, the proposed solution intends to work in the broadest way possible using low-cost devices, acting in a pervasive way in a physical context, achieving reliable results, ensuring their welfare, and simplifying the caregivers' tasks in their daily life.

3

Proposed Solution

The technological solution proposed in this chapter aims to respond directly to the need that the caregiver has to be supported in her/his tasks and particularly in the supervision of the person in her/his care. Thus, it is intended to design a platform capable of responding to the needs of the caregiver with regard to obtaining information about the person in her/his care, as well as tools to support triage and decision making, providing conditions for constant and more efficient monitoring.

3.1.Conceptual Model

The platform should be based on low-cost IoT technology (see Figure 15), supporting the caregiver's tasks, and the older adults' monitoring while keeping them autonomous. The platform must be able to take illations regarding the activity and potential risks or atypical situations through the continuous monitoring of the daily routine of an older person in her/his own home. In a pervasive way, the platform should intervene in a first instance to carry out an autonomous triage, which would allow real-time alerts to be triggered whenever necessary, enabling action by the caregiver or competent entities, in a timely manner.

Is possible to determine a wide range of measures to be obtained in any home using low-cost devices from IoT platforms that are proposed for application in smart homes. Is possible to use aggregated information, even analyzed in other contexts, such as analysing the daily routine. Another possibility would be to take advantage of binary sensors, using the implementation of proprietary systems, further lowering the cost of the final solution, through the intended purpose, always allowing the modular growth of this solution.

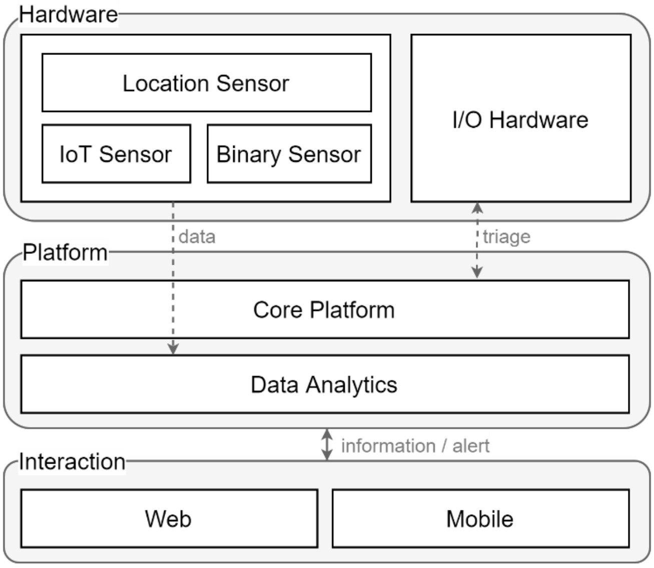

Figure 15 - High-level architecture diagram

The routine analysis will work at different levels of granularity. In a first instance, perception of the user's physical context, through the indoor location using signaling devices (beacons), allows identifying with a high degree of reliability the division or concrete area of the division in which the older adult is. For this solution, it is required to use an intermediate device that collects information (gateway) from the different signals existing in its physical context and sends that information to the platform. Ideally, a wearable device with wide autonomy would be selected to implement this task.

There is a set of activities that can be carried out in each division of the house, which is previously identified and configured on the platform. Once determined the division in which the older adult is, data is collected from the sensors present in that same physical space to determine what is the activity in progress. The analysis of values extracted from the deployed sensors allows the classification of concrete activities. A set of metrics are used with the purpose of obtaining a more precise classification.

In the first instance of implementation, the platform has mechanisms to complement the task of recognizing daily activity. In order to validate the illations drawn concerning the user's activity, the platform invokes a simple validation from the user, using voice interaction through a "yes"/"no" input, that allows determining whether the analysis performed was the correct one, or not. Such interaction is essential to ensure the platform's continuous learning and, consequently, the reliability of the results, with the older adult being an actor in the process of training the classification algorithm.

The analysis and classification process is based on the attribution of probabilistic weights to each one of the activities, given the physical context and daily routine of the older adult. This probabilistic model is supported by the recognized pattern based on the extracted data. The accuracy of the results obtained depends on the amount of valid data that feeds the platform which remains in a constant learning mechanism.

The detection of changes to the known pattern triggers mechanisms to detect problems. At this point, the platform has an essential role, acting as an intermediary between the older adult and the caregiver, performing the first triage. Triggers voice interaction-based mechanisms with the older adult, to identify the existence of potential problems. The platform will inform the caregiver or other responsible entities, both in the case of receiving feedback and in its absence. The type and direction of the provided notification change according to the severity of the situation detected.

The older adult is allowed to identify a problem or difficulty at any time, and the platform is responsible for notifying the caregiver. A mobile application allows caregivers to receive notification alerts in real-time, contextualized according to the problem's urgency level. The caregiver will have the possibility to monitor and follow the person's daily routine in care and trigger requests for feedback when convenient.

3.2.Scenarios of Action

The conceptual model serves as the idealization of a technological-based solution that intends to respond to real-world problems, societal challenges, allowing a direct application to scenarios commonly known by people. The platform is designed taking into account the following scenarios.

Scenario I - Pervasive measurement of a critical situation, using triage, through the permanent analysis of daily routine data

> An older adult lives alone in her/his house and will bathe in the late afternoon, around 6 pm, in the normality of her/his daily life. Upon entering the bathroom, the platform recognizes her/his presence in that space and activates the collection of data from the sensors of that same room. These, when analyzed by the platform, associated with increased temperature and relative humidity, as well as the timestamp of the collection of information, can determine with a certain degree of certainty, given the usual routine, that the older adult is bathing. Thus, once the action that may be occurring is classified, the platform knows that it has a duration of approximately 20 minutes, on average.
>
> During this activity, the older adult falls into the bathtub, losing consciousness. Happens that, after 35 minutes, there is no information that the older adult has left this room, as well as the indicators received from the sensors do not show a decrease in the values collected. As this is a considerable time interval compared to the standard, this situation is interpreted by the platform as atypical and may be representative of a dangerous situation.

As a triage attempt, the platform triggers a voice triage mechanism in which it questions the older adult with "Is everything okay?", audibly from one of the columns in the house, nearest to the room in which s/he was located. If conscious, s/he would know that the platform awaits her/his feedback. In order to do so, it is enough for the older adult to respond by voice, audibly, with a "yes" or "no". Having lost her/his senses, her/his feedback is not obtained. The situation is classified as being critical and, thus, her/his caregiver is immediately informed.

The caregiver, who had just arrived home at the end of the working day, receives the alert with the situation under consideration, through the mobile application. The caregiver can choose to go to the older adult's house if s/he can do it in a useful time, or choose to immediately activate another entity (firefighters, INEM, …). Around 7 pm, the older adult would be rescued, receiving the help s/he needed, in useful time.

Scenario II – Help request by voice due to a need of the older adult

Around 1 pm, an older adult male accidentally drops water on the floor when making lunch. As the older adult passes over the wet floor, s/he slips and falls.

He immediately realizes that he cannot get up, nor does have any mobile device, which he could use to ask for help. By voice, he triggers a call for help from the platform, using the word "help", predefined in the application for this purpose.

The platform triggers its triage mechanism, questioning whether he intends to inform the caregiver or start other means of assistance. In this case, the caregiver is his son and, knowing that he is in the work period and would take about an hour to arrive, he chooses to call another entity to be rescued. The platform thus simultaneously directs a call to 112 and sends an urgent notification to the caregiver. In a short period, the rescue workers arrive at her/his house. His son, who was at lunch at work, is warned and immediately goes to the hospital, where he can accompany his father.

Scenario III - Request for feedback from the caregiver regarding the state of the older adult

At the end of the working day, a caregiver feels worried about her mother, as she usually calls her at lunchtime and on that day she did not. Being late to pick up her children from school and still needing to go to the grocery store, she opens the mobile app and makes a feedback request.

Her mother at home, through the platform, receives the following question: "Your daughter asks if everything is okay?". She, using the interaction by voice or through the physical interface, responds yes.

So, her daughter receives soon after, through the smartphone, the notification of her answer, which tranquilizes her.

Scenario IV - Analytical assessment of abnormal situations

As a habit, the caregiver has to analyze the statistics of her/his uncle's activity weekly. When analyzing the statistics of the last week, s/he notices a marked deviation from the pattern of time spent in the bedroom, which leads him to question whether everything is okay with the older adult in her/his care.

Since the next day is Saturday, s/he decides to go to her/his uncle's house and talk to him about the time spent in the bedroom. As they talk, the caregiver realizes that the uncle has been sadder and feeling more alone, not been visited for some time.

By analyzing the statistics and, consequently, having visited her/his uncle, as well as contradicting the older adult’s state of mind, s/he realizes the need to schedule a family lunch for the following day, which would last all afternoon.

Scenario V - Machine learning of the daily routine of the older adult

In one of the first uses of the system, the platform realized the older adult entered the kitchen around 12:30 and stayed there for about 40 minutes. In the end, through voice interaction, it questioned if s/he was cooking. As the feedback was positive, the next day, and since around the same time the situation was repeated, the platform was able to classify with a high degree of certainty that the older adult was doing the same activity. Thus, as time goes by, it is easier to recognize a pattern and, therefore, deviations from it.

Scenario VI - Statistical analysis of the feedback obtained

The caregiver has parameterized, through the mobile application, to receive statistical information on his grandmother's daily activity time every day at the beginning of the night. Today, more carefully, he realized the time of daily activity was gradually decreasing. By accessing the platform's statistical information, he realized that this situation has been going on for the last two weeks. The movement within the house itself has been more contained. Given this, he exposes this analysis when visiting his grandmother. She confesses that, lately, she has felt a permanent pain in her knee, but did not tell about this situation because she thought it would attenuate and did not want to worry her relatives.

This way, her grandson makes an appointment where a series of physiotherapy sessions is recommended. This follow-up allowed the improvement of a situation that would tend to get worse.

3.3. Solution Behaviour

Figure 16 illustrates the fundamental steps of the proposed solution’s workflow, which can be divided into six distinct moments that are interconnected in a continuous flow.

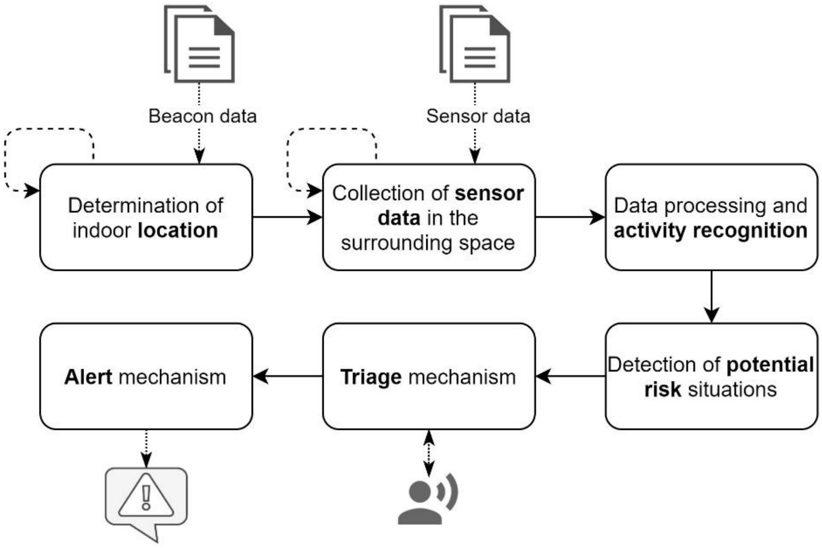

Figure 16 - Fundamental steps in the functioning of the proposed solution

3.3.1.Determination of Indoor Location

The platform can determine in real-time, with a high degree of certainty, the older adult's location in her/his home. In order to understand where the older adult is located, a BLE beacon device is placed per room, at a strategic point of the room. Through the study of the technology involved, conducted in the previous chapter, it is possible to determine, with some accuracy, the proximity of the person to each one of these emitters, thus identifying the division where s/he is.

The signal receiver is located in the bracelet (wearable device) that should be used by the older adult permanently. Every time the person is in the proximity of a beacon, the bracelet device sends the detection data to the platform, so that the remaining stages of the monitoring process can be initiated. In addition to determining the location of the older adult, it is also possible to calculate the duration of the older adult's permanence in a particular room (see Figure 17).

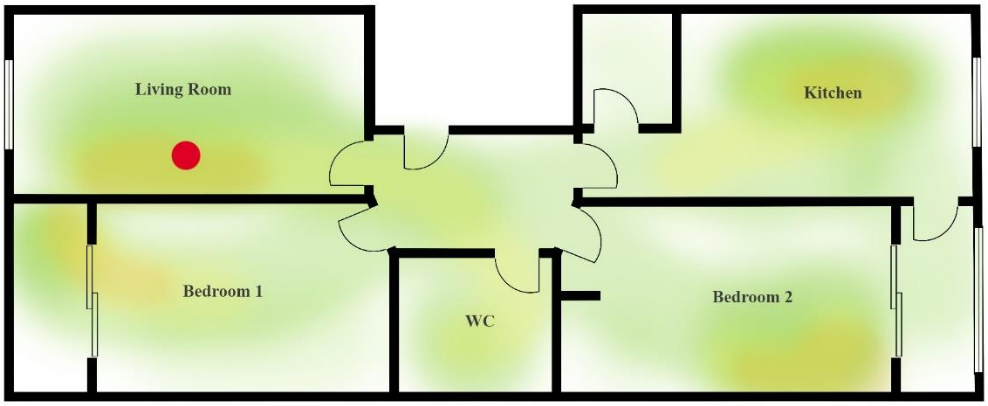

Figure 17 - Example of a heat map representation from the indoor localization data

3.3.2. Collecting sensor data in the surrounding space

When the older adult's movement in a room is detected, the reading and collection of data from all sensors in the room are triggered by the platform through the gateway located in the physical space.

The number and typology of existing sensors per room have to be carefully considered, being in the number and diversity necessary to ensure accuracy in the readings in order to be able to detect as many critical situations as possible, keeping the cost of the implementation of the solution as low as possible.

In the scope of activity recognition, a broader approach (not focused on concrete activities) based on location perception, related to some environmental data, allows the determination of some activities, relevant to the perception of potential risk, without the need to use a large number of devices, and consequently a drastic increase in the cost of implementation.

The complementary use of some types of sensors, such as proximity, pressure and contact, can be quite beneficial in determining more specific activities. However, this approach requires a direct relationship between sensors and object (or set of objects) involved in the activity executed, as well as the physical space in which it would occur. Thus, it would increase the number of devices used and the cost and complexity of implementation in the physical space.

Aware of the inherent costs, there is a wide range of possibilities for classification and analysis with the addition of other types of sensors, in doors and windows, such as movement and proximity sensors, among many others, specific to the intended concrete analysis. Although it would significantly increase the accuracy of the platform's analyses, the cost-benefit ratio must be considered according to the specificity of the intended deployment. Therefore, the modularity of the designed platform is essential, not only for the implementation's versatility but also for responding to the necessary increments, according to the user's needs, arising from the natural aging process.

In general, we aim to determine, with the greatest fidelity possible, the higher number of critical situations with the smallest number of necessary devices, reducing the solution's costs.

3.3.3.Data Processing and Recognition of Activities

After determining the location of the older adult and activating the sensors in the same room, the process of classifying the activity currently being executed is initiated, based on data collected by the sensors. This process is fundamental because it is only possible to determine potentially critical situations, knowing the activity executed at the moment, to be later determined if it is practiced with the usual pattern.

The normal pattern of a specific activity is usually determined by a known set of value ranges, established a priori, and automatically adjusted as the information is collected. This set of previously classified data is known as a training set and serves as the basis for supervised Machine Learning (ML) algorithms that will support the classification process.

As a rule, the application of this type of algorithms can generate classification and regression results. The first, as already explained, deals with the mapping of similar elements in specific categories, such as, the case of determining the activity performed. The second consists in identifying a trend for the data, which even allows making predictions based on historical data, which can also be a way of identifying potentially critical situations.

Is possible to identify a pattern by knowing the inputs that give rise to a known result. Thus, data received at the moment work as a reference and, therefore, may determine potentially critical situations, based on the abnormal oscelations of a given data combination (see Figure 18).

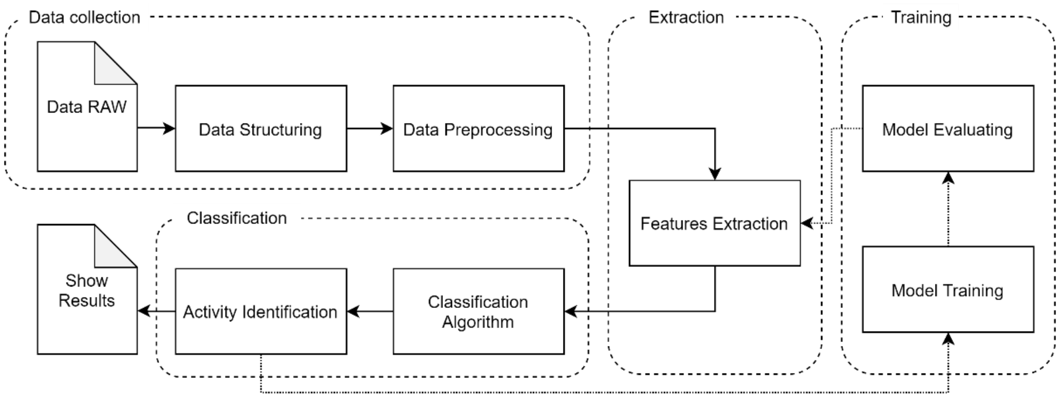

Figure 18 - Flow diagram of the activity recognition system

3.3.4.Detection of Potential Risk Situations

The identification of a potentially critical situation may be inferred from information derived from actual data readings or a set of related data. This identification can be classified in two distinct ways:

- Knowing a risk pattern, identifying it;
- Knowing the normal pattern of use, identifying significant deviations from it.

Depending on the type of technology used, it is possible to list previous situations of potential risk, for each of the rooms (Table 2). A simple way to identify significant deviations from the daily routine's standards of the older adult may be by the time spent in a certain room, correlated with the day period. Whenever the time spent or a particular activity has an extremely long (or short) duration compared to the one usually practiced and recognized by the platform, it may be a significant indicator.

The combination of the time factor with collected data, by another type of sensors, may add some significant information. Knowing, for example, that the older adult is in the bathroom, by collecting information from an environmental sensor of temperature and relative humidity, it is easy to classify that the resulting activity is the daily showering. By knowing her/his daily routine pattern, the system has information regarding the average duration of this activity. A value significantly higher than the usual duration may indicate a critical factor and may have at its origin a situation, such as a fall or indisposition.

The combination of the perception of her/his location in the room and the reading of a load sensor placed on the bed easily allows identifying whether s/he is at rest or not. Measurements such as lying down for an abnormally long (or short) period, staying in bed (in the morning) at a time that significantly exceeds the usual time of getting up, or even the absence of this activity at the usual time known for it, may indicate potential critical situations.

The lack of detection of her/his location in the house may indicate her/his absence from it. Thus, the perception of failure to return to her/his home (when not usual), or even leaving outside regular hours may be indicators of risk.

Table 2 - Technology and potential risks detected per room

		Technology			
Room	**Factors leading to potentially critical situations**	**Location sensors**	**Environmental sensors**	**Other sensors**	**Wearable**
Living Room	• Too much inactive time	Beacon			Bracelet
Bedroom	• Abnormally long bedtime in the morning • Abnormally short time lying in bed • The person has not gone to bed at the usual time	Beacon		Load sensor	Bracelet
Kitchen	• Sudden rise in temperature while cooking	Beacon	Temperature sensor		Bracelet
WC	• Long time in the bath • Prolonged stay in the room, which may coincide with situations of fall or indisposition	Beacon	Temperature and relative humidity sensor		Bracelet
Outdoor	• Failure to return to the dwelling • Moving out of the house at an atypical time	Beacon			Bracelet

3.3.5. Triage Mechanism

A triage process begins when a potentially critical situation is perceived. Here, the platform has a fundamental role in supporting the caregiver's task, managing to have a primary intervention between the older adult and a caregiver, to interpret both the existence of a real problem and its severity.

This intervention is fundamental to eliminate false positives with the caregivers, which removes an enormous intervention responsibility (being reserved for strictly necessary situations), which could originate a contradiction to the platform's usefulness. On the other hand, this mechanism also allows the triggering of the necessary alert and notification mechanisms, given the seriousness of the situation detected, in an attempt to intervene more promptly and appropriately for the problem.

The intervention with the older adult is carried out using a voice interaction device, in which s/he is asked for simple feedback regarding her/his condition. The lack of response to this request also leads to warning mechanisms (see Figure 19).

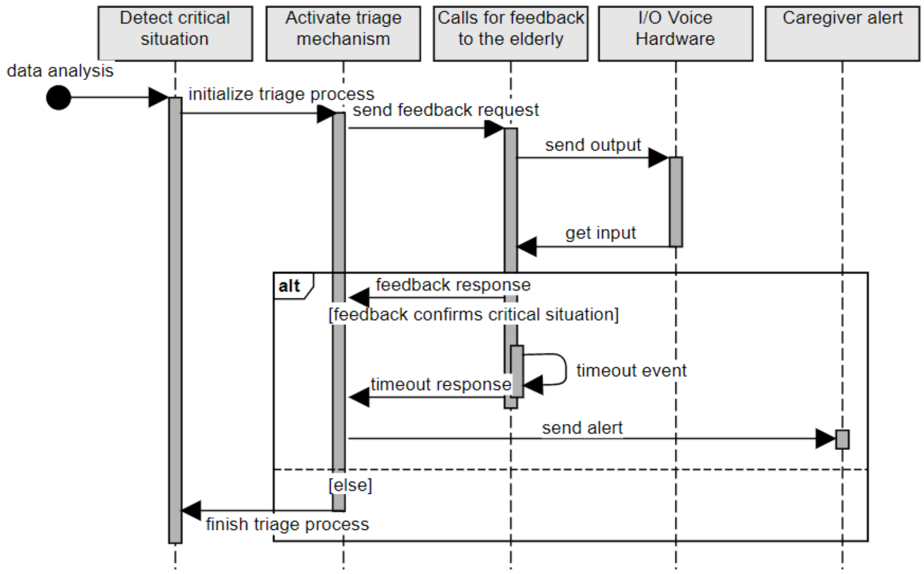

Figure 19 - Sequential diagram of the triage process

3.3.6. Alert Mechanism

The alert procedure is transversal to different workflows of the platform, being responsible for all the communication between the platform and the caregiver. The proposed platform is equipped with a set of tools at the level of data analysis capable of assessing different situations, statistics and other relevant data. The caregiver may be interested in receiving this information periodically, in addition to the signalization of situations of real problems that require intervention at the moment. Therefore, it is fundamental to create different notification/alert mechanisms regarding the information presented, and the need (or not) for intervention by the caregiver.

The alerts that not require immediate intervention, such as informative and warning alerts, can be received on the caregiver's mobile device, in the form of a push notification[10], configured by the caregiver. Danger alerts require immediate intervention by the caregiver, so the system needs to ensure their reception by the caregiver through feedback input.

To allow effective interventions, it would be fundamental that in the absence of a response from the caregiver, or in situations classified as a high degree of urgency, the alert could be triggered, in the future, directly to competent entities for intervention and support.

3.4. Minimal Implementation

The following describes the minimum necessary implementation considering the respective modules to achieve end-to-end satisfaction of the proposed platform's basic requirements to be functional and reach its purpose. In this way, it is possible to identify the core of the platform and modularly enhance its future growth, satisfying the needs of the whole process, which is an active aging and inherent needs.

The base implementation contemplates components of each of the layers - *home-side*, *cloud-side*, *server-side* and *client-side* - to obtain a functional *workflow*, end-to-end.

- On the *home-side*, it is necessary to integrate a set of gateways to collect information and compute the respective data, either to determine the location in the indoor space, from beacon devices, or to collect data from environmental sensors, such as temperature and relative humidity sensors.
- On the *cloud-side*, it is needed the integration of a component responsible for triggering alert mechanisms (notifications) to the caregiver.
- On the *client-side*, it is essential to have a notification system (mobile application) so that the information coming from the platform can reach the caregiver in useful time.
- On the server-side, the ICAN(b)E and ICAN(se)E modules that integrate it have to be developed, being the first responsible for the aggregation, integration and complete operation between each of the components of the system, and the second, responsible for all the data analysis work.

The functional prototype of the conceptualized platform will be designed based on this core setup. It will serve as a proof of concept. Thus, it will be possible to understand its functioning as a whole,

[10] Push or server technology describes an Internet-based communication style where the request for a given transaction is initiated by the publisher or central server.

verify its efficiency in action and the response it can give to the proposed challenges, and analyze its potential for growth and extensibility.

4

ICAN(b)E – Support Platform

ICAN(b)E, acronym that identifies the conceptualized platform, comes from a pun from the terms "*I can be*" and "*ICane*". The first, on the side of the older adults, has the cognitive sense of being able to stay/being in their own home, in the sense that they can maintain their independence and active life in society, being in their home, without the need for institutionalization. The second term, both from the perspective of the caregiver and the older adult, can be interpreted as an intelligent walking stick, a tool in their daily lives, which with the use of technology, allows giving a level of support to both the role of the caregiver and the daily life of the older adult.

This platform aims to respond both to the need of the caregiver, to have a set of tools that support her /him in her/his tasks, as well as to the need for monitoring and tracking the older adult and her/his activity. Thus, this chapter presents the implementation of the conceptualized platform, as a whole, identifying its primary flows and respective functionalities, as well as the secondary and parallel processes.

4.1.Platform's Architecture

The architecture for implementing this platform extends and aggregates components of four distinct integration layers (see Figure 20) to create a modular and widely extendable system at the level of functionality. One of the focuses was the use of low-cost technology, existing and validated by the market, not only at the level of hardware, but also at the level of technologies and software consumed under the format of services.

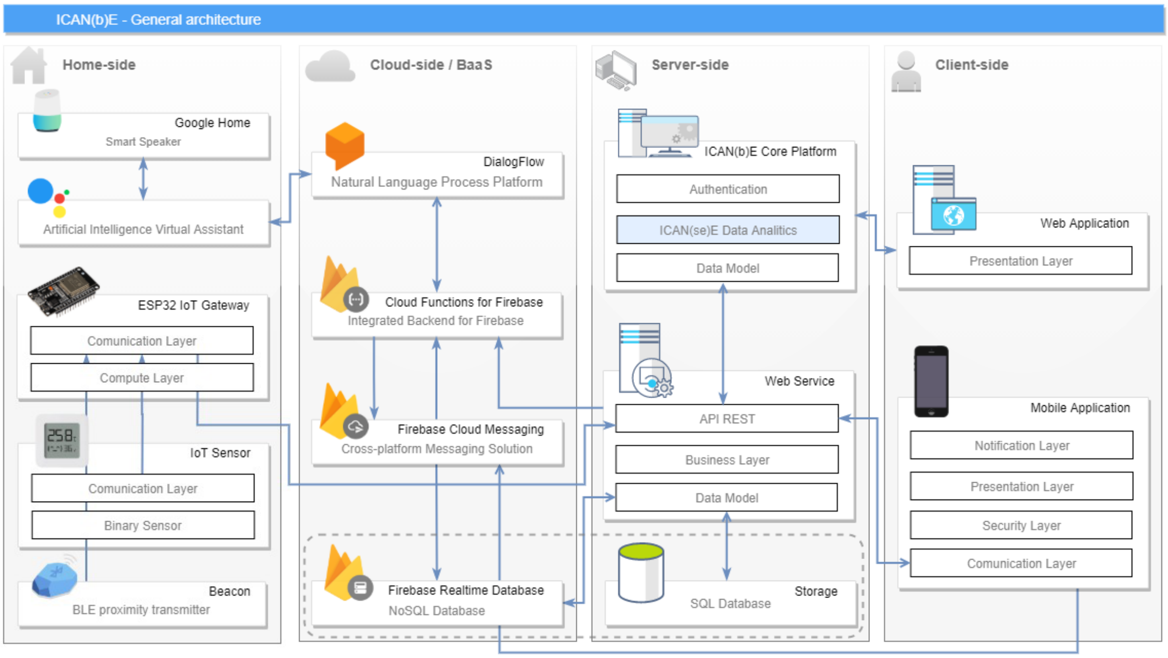

Figure 20 - General architecture diagram of the ICAN(b)E platform

The implementation of all the physical hardware is made on the home-side, allowing for direct or pervasive interaction with the older adult. In this layer, it has been considered the environmental sensors, such as temperature and relative humidity sensors, and location sensors, such as beacon devices. These devices communicate by Bluetooth low energy (BLE) with an ESP32 [11] microcontroller programmed for this purpose, responsible for reading and processing the values collected and, finally, for sending them to the server. Also provides a voice interaction module (I/O), allowing the collection of feedback from the older adult, using this interface (VUI). For this, an intelligent column (Google Home Mini) is used, which integrates directly with the artificial intelligence services Google Assistant[12].

Part of the platform support architecture is centralized in cloud computing, a paradigm increasingly common today due to its flexibility and computational power (Attaran, 2017). Here, the platform takes advantage of a set of Firebase services, used in the back-end architecture as a service, removing computational weight and complexity from the implemented system's back-end. Also uses the cloud-hosted service Firebase Realtime Database, a non-relational database (NoSQL) to persist the information that needs real-time synchronization in all components that are aggregated in this

[11] Created by Espressif Systems, ESP32 is a low-cost, low-power system on a chip (SoC) series with Wi-Fi & dual-mode Bluetooth capabilities.

[12] Google Assistant is a personal virtual assistant developed by Google that can perform day-to-day tasks such as calling people, messaging, searching Google, and even chatting with the user. It was announced at its developers conference in May 2016.

platform. Also uses DialogFlow, a platform for understanding natural language, to perform the processing that comes from voice interaction with the older adult.

Is on the server-side that the central implementation of the platform is located. Here, it can be subdivided into four distinct areas of operation:

- ICAN(b)E core platform, which is responsible for the centralization of all components and modules, information aggregation and production of visual and statistical content;
- ICAN(se)E module, which is responsible for the whole process of data analysis using automated machine learning techniques to analyze and classify the activities executed in the daily routine of the older adult, as well as to detect anomalies to the patterns of this same routine, which may mean potentially critical situations;
- Web service that uses REST as a means of communication, which performs the management of persistence and data consumed and used on the platform, stored in the platform's database or into the synchronization database in the cloud, containing an integrated ORM[13];
- Relational database as a repository of data necessary both for the platform to work and for historical data.

The caregiver has access to either a web portal or a mobile application. In both, it has a set of features ranging from alert and notification of atypical or potentially dangerous situations in real-time, availability of results and statistical values, requests for feedback from the caregiver, to a detailed analysis of the older adult's daily routine. The mobile application serves as a primary form of contact, if necessary, with the caregiver.

4.2.Components

The platform has a set of components that integrate and communicate through different communication protocols. These components are spread over four different layers. The complete workflow, which aims to bring information related to the older adult, to their caregiver, must necessarily go through all of them. Is on the server-side that the aggregating platform is located, with the necessary technologies not only to aggregate information but also to communicate with the other connected platforms. Each one of these layers will be analyzed as follows.

[13] Object-relational mapping – in computer science is a programming technique for converting data between incompatible type systems using object-oriented programming languages. This creates, in effect, a "virtual object database" that can be used from within the programming language.

4.2.1. Home-Side

This layer includes all the existing components in the older adult's home side, being responsible for the integration of all the interaction peripherals with the older adult (as voice interaction), as well as all the peripherals responsible for the collection of environmental and location data, described below.

- **Smart Speaker**

Nowadays, there is a large number of smart speaker solutions in the market. Most of them allocate artificial intelligence, and they are able to support daily activities through input/output (I/O) actions. One of these solutions, which was used in the proposed implementation, is the Google Home Mini, a simplified version of the Google Home column. Generically, Google Home is a device called "smart speaker" with Wi-Fi connection that allows, through an artificial intelligence system, the Google Assistant application to have access to real-time answers about time, traffic, sports, finance and local business, connection and control over other intelligent devices, among others. The choice fell on this solution due to its versatility of integration with existing solutions, either from Google development environment or others, which simplifies the implementation of specific resources using this equipment.

- **IoT Sensors**

Regardless of the purpose, nowadays, there is a wide range of low-cost devices and sensors, capable of being customized and integrated into various IoT solutions. The market validates their technology and their reliability is well-known. Most of them are directly integrate with solutions often developed by the market; however, possessing open-protocol technology, it is possible to send and extract information from them to third-party solutions.

To collect environmental data regarding temperature and relative humidity, Xiaomi Mijia 2 intelligent -wireless sensors were used, which communicate by BLE 4.2, with a reading range of temperature in [0º, 60º] and relative humidity in [0%, 99%] RH, with reliability of 0.1ºc and 1% RH, respectively. This device can collect and send information with regular periodicity, whenever requested by a mobile application or another system that communicates via Bluetooth. With a single battery, it can guarantee an autonomy of approximately two years.

To determine the indoor location, accent systems[14]' iBKS 105 BLE beacons, based on the Nordic Semiconductors[15] nrf51822 *chipset*, are officially known to be the first iBeacon and Eddystone

[14] https://accent-systems.com

[15] https://www.nordicsemi.com

compatible beacon (UID, URL, TLM, EID) at the same time. Therefore, it is versatile for implementation in a wide range of distinct solutions, with an autonomy of 30-40 months (depending on the Tx power within 1s) using a single battery.

- **Gateway IoT ESP32**

In its simplest form, an IoT gateway can be just hardware or software to collect and aggregate data from input and output devices such as sensors. The gateway communicates the data from the other devices, either to servers in local data centers or in the cloud, thus serving as an intermediary. The flow of information can circulate in the opposite direction or in a bidirectional way, and the gateways can trigger information to the connected devices (sensors).

In this implementation, the ESP32 Dev Board module was used as *gateways*, which is a single combined WiFi 2.4 GHz and Bluetooth (4.2) chip, designed with the ultra-low-power 40 nm TSMC[16] (see Figure 21). Was designed to achieve the best RF power and performance, showing robustness, versatility and reliability in a wide variety of applications and low power scenarios, being widely used for mobile, electronic (wearables), and IoT applications. Its components combine low power technology to optimize their energy consumption and can act in scenarios where, for example, in an IoT sensor application scenario, ESP32 can be awakened periodically and only when a specified condition is detected.

Is composed of a microprocessor of low consumption Xtensa 32-bit LX6, 448 KB of ROM for *booting* and *core* functions and 520 KB of SRAM on-chip for data and instructions. With the use of specific libraries to work with wireless communication resources such as Wi-Fi and BLE, and client-server communication (HTTP), which occupy a significant size by default, the storage resources may be insufficient for the compilation of the *source code.* This being one of the major limitations of this low-cost module. The allocation of variables in EEPROM memory was also used in addition to the full optimization of the code implemented in C programming language (with the respective good practices of dynamic memory allocation) and restructuring of some libraries used. However, this set of techniques was not sufficient for the necessary compilation. In order to overcome this limitation, the implemented *gateways* were adjusted in the parameters of the partition table, which come as a factory *default* distribution. Thus, by readjusting the allocation of each of the partitions, it was possible to get some space additional for the compilation of the program, which allows the use of BLE communication resources with Wi-Fi communication in order to collect data directly from the sensors and be able to send them to WebServices REST. Despite the limitations of a low-cost computing module like the ESP32, its use in this platform implementation has gained importance, in

[16] Taiwan Semiconductor Manufacturing Company (TSMC): https://www.tsmc.com

detriment of the use of others with more resources, such as Raspberry Pi[17], not only due to the significant cost difference, but also to the fact that its architecture is the basis of countless devices, such as programmable wearables. In this implementation, the ESP32 was also used as a smart band simulator (to be developed in a future phase), and was worn by the older adult, on the wrist, with a small battery, which guaranteed the necessary autonomy.

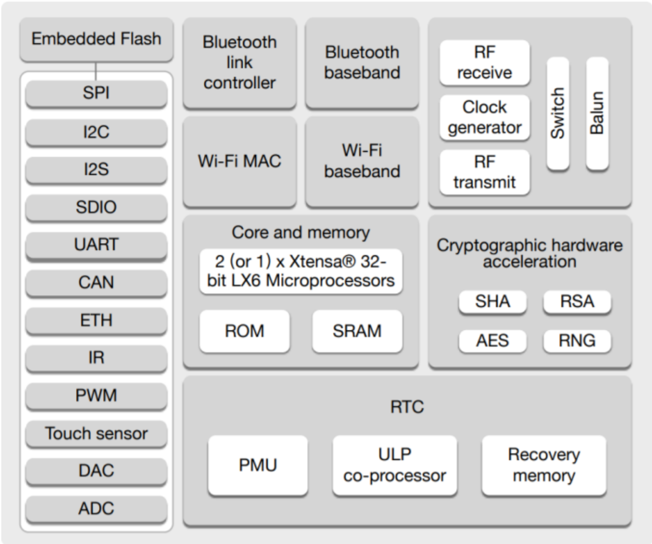

Figure 21 - ESP32: Functional block diagram [Source: Espressif, 2019]

- **Indoor positioning detector (beacons) -** For the constant and real-time determination of the location of the older adult in her/his home, the ESP32 gateway in the user's possession, performs verification with a fixed periodicity of 30 seconds, to determine which beacon device is closest in the physical context, and consequently determine in which room s/he is. When initiated, the gateway triggers an initial procedure to connect to the wireless network, knowing the SSID18 and password. If it cannot establish a connection, it repeats the process in 500ms. In case of success, it establishes a connection with the Firebase server using the host and authentication key, where it obtains information regarding the last detected beacon. Once booted, runs a scanner routine for BLE devices, periodically, where it will obtain information from all BLE devices at its reach. If it gets results, will analyze each of these devices in order to check if this device is a valid beacon, and with a UUID known by the system. Being a valid beacon, checks if the RSSI of this new device is greater than the RSSI of the previously known device, which means being at a lower distance from the receiver.

[17] Raspberry Pi: https://www.raspberrypi.org/

[18] Service Set IDentifier (SSID), is a sequence of characters that uniquely names a wireless local area network (WLAN).

Also checks if this device is different from the previous one. Must contain the same Major value (identifier of the user's instant) and different Minor value (identifier of division). There is a new proximity device if the requirement is fullfilled, being consequently detected the change of division in which the older adult is. This value will be sent and stored on the server.

- **Environmental data collector (temperature and relative humidity) -** The reading of environmental data values from existing sensors in this same space, where the *gateway* is located, starts when a new location of a user is detected. The similarity of the *gateways* for position detection begins by establishing a connection to the wireless network. When established, each of the existing *gateways* by division, checks which is the last known location of the older adult, requesting this information from the server, with a periodicity of one minute, thus optimizing traffic and energy consumption. The *gateway* installed in the space where the user is, automatically starts the reading of the sensors present in this space, being this reading performed, with a constant periodicity, until a new location is detected for the user in question. Each *gateway* knows the identifier of the device to which it will connect, seeks to establish a BLE connection with it, starting the reading of raw data from the sensor. The process of computing and data processing is initiated when data is received. Will obtain the conversion of the reading of the temperature and relative humidity values. These values will be sent to the server to consume the data by the platform, using an HTTP communication with Webservice REST. The procedure repeats with a periodicity of 10 seconds, to follow the evolution of the data obtained.

4.2.2. Cloud-Side

This layer is composed of all the non-proprietary services used by the platform. They are services of third parties, with which the system integrates through requests, producing some computational work in the cloud, and returning some feedback or content. This implementation is essentially about services included in the Google Cloud universe, such as Firebase.

Realtime Database

To maintain the availability and consistency of the data required to platform functioning, among all the devices (components) that constitute it, with the need for synchronization in real-time, and to use mechanisms to trigger actions (*triggers*) through data changes, their persistence is performed in a NoSQL database hosted in cloud, using the Firebase Realtime Database[19] service. In this way, the storage and synchronization in real-time between the database and all the components of the platform

[19] https://firebase.google.com/products/realtime-database

is ensured, maintaining the coherence of the information. This data persistence technology is shared between the ICAN(b)E platform, as well as by the notification system (mobile application) and the data consumption *gateways* themselves. This mechanism uses collections and documents to structure and query data, the sending and requesting of data is done in JSON format. This allows data sharing with other Google Firebase[20] environment technologies, thus facilitating their integration.

Firebase Cloud Messaging

Firebase Cloud Messaging (FCM) is a platform that provides a reliable connection, with low battery consumption and traffic, between the server and devices, which allows sending and receiving messages and notifications either on iOS, Android or the web, without cost. These messages can be directed individually or by custom segments, based on groups created or based on demographic data and user behavior. The sending is done in real-time, and it is also possible to schedule periodic sending, and through the implementation done in the client (receiving device), these notifications can be customizable, in terms of content, presentation and respective notification. When a potentially critical situation is detected, the caregiver is notified, with the level of severity identified after the triage process, of the respective situation, regardless of whether the mobile application is running in the background or not on your device. This notification reaches your mobile device via a message and its push notification[21]. Periodic notifications are received by the caregiver, regarding the current state of the older adult in her/his or her care, through parameterization and preferences made by him or her in the respective customization module.

Cloud Functions

The Cloud Functions integrated into Firebase, is a server-less structure that allows you to automatically execute backend code in response to events triggered by Firebase features, Google Cloud or HTTPS[22] requests. These functions, developed in JavaScript are stored in the cloud, and being triggered by HTTPS, can be invoked from any proprietary backend. Thus, in this implementation, they serve as an intermediary mechanism for managing actions between platform and voice interaction system, or for managing and sending notifications to the caregiver, since both integrate with Google environment tools. These functions take advantage of the access to the database in real-time persisted in Firebase, to access data from the users of the system, and direct the requests sent by the ICAN(b)E platform.

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[20] https://firebase.google.com/

[21] A simple way to send the user relevant information without having requested it.

[22] Hyper Text Transfer Protocol Secure (HTTPS) is an HTTP protocol implementation over an additional layer of security that uses the SSL/TLS protocol

Dialogflow

Dialogflow is a natural language processing (NLP) platform that facilitates the design and integration of a conversational user interface (VUI) with any proprietary system. With the ease of integration with other technologies in the Google Cloud environment. Integrates directly with the existing intelligent column in the older adult home, to produce personalized interaction through the customization of interactions with Google Assistant, such as requests for help. When receiving an input, it analyzes it with internal mechanisms of artificial intelligence and machine learning, performing the processing of natural language and thus recognize keywords that when verbalized, provide actions. The separation of actions and mechanisms is facilitated by its integration with Google Cloud Functions technology, so it is possible to send and request data to Webservice REST, the persistence of data and actions on the platform. The reverse flow is also possible, that is, to be the own platform to trigger output in the intelligent column, through dialogue flow, to transmit information to the older adult and trigger feedback requests (see Figure 22).

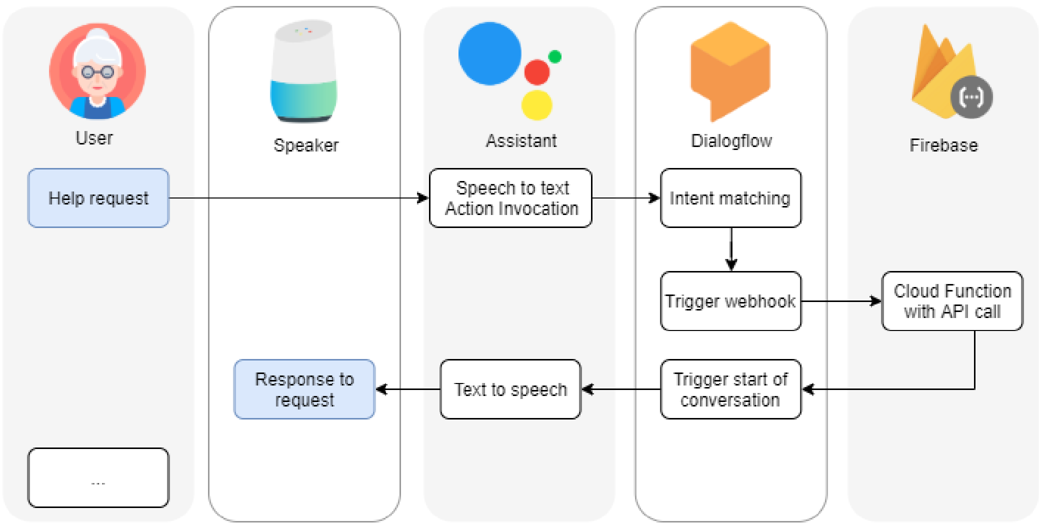

Figure 22 - Part of an older adult user's aid request flow

4.2.3. Server-Side

This layer consists of the implementation of the platform *backend* developed, consisting of a set of components of which the platform itself and its modules (server), *Webservice* API REST for consumption and aggregation of data and database for persistence. All these will be described in more detail below.

ICAN(b)E

Consists of the backend of the conceptualized platform, responsible for data uniformity and integration of all system components, this is the module responsible for interoperability between them, establishing and managing information flows. Implemented using Microsoft ASP.NET Core[23] 3.1 with an MVC[24] architecture, implemented essentially in the C# programming language at the *controller* level and HTML[25] , JavaScript[26] and CSS[27] at the *view* level.

User data is managed by the Firebase Authentication system, staying in the cloud and ensuring its integrity, as well as the reuse of the user identity as a form of access in all components of the ICAN(b)E platform. This service uses its own security and encryption system, which is heavily used in the system development sector, and therefore, respectively validated, providing the guarantee of not compromising the identity of the platform users.

Makes available to the caregiver, based on the data analysis work, produced by the ICAN(se)E module, all the information related to the older adult in their care, in the form of graphs produced with the use of multivariable information visualization libraries, in a dynamic way as the D3.js [28]. Allows a set of analyses and statistics, as well as the presentation of historical data related to the daily activity of the older adult, among which the determination of the current location of the older adult on a map (*floorplane*) as well as the frequency of stay in the area (*heatmap*), presentation for a certain period (24 hours by default) the state, location and activity practiced, comparison of the pattern of activity present with the historical known to the same user. Also generates and presents all the information regarding critical and potentially dangerous situations, detected and later reported.

Has mechanisms for sending (*broadcasting*) messages and/or notifications, to interact and trigger actions in the notifier application installed in the caregiver's mobile device. These can be sent with different levels of severity, if necessary. Is also responsible for triggering triage mechanisms with the older adult. These are triggered when potentially critical situations are detected, coming from the data analysis performed.

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[23] The open-source and cross-platform version of ASP.NET, a popular web-development framework for building web apps on the .NET platform: https://docs.microsoft.com/en-us/aspnet/core/?view=aspnetcore-3.1

[24] Model View Controller (MVC): https://dotnet.microsoft.com/apps/aspnet/mvc

[25] HyperText Markup Language (HTML): https://developer.mozilla.org/en-US/docs/Web/HTML

[26] JavaScript is a structured, high level scripting programming language with low dynamic and multi-paradigm typing: https://developer.mozilla.org/en-US/docs/Web/JavaScript

[27] Cascading Style Sheets (CSS): https://developer.mozilla.org/en-US/docs/Web/CSS

[28] D3.js is a JavaScript library for producing interactive and dynamic data visualizations in web browsers: https://d3js.org/

ICAN(se)E

This is one of the central modules of the platform, responsible for all the work of analysis and data processing, categorizing and classifying them, to interpret and remove links regarding the information received. This module provides the platform with mechanisms and heuristics capable of identifying significant situations for remote monitoring by the caregiver. Is also responsible for triggering, together with the older adult, the triage mechanisms for immediate action, and consequently, alert the caregiver to relevant situations.

The implementation of the module focuses on the use of the open-source framework and cross-platform Microsoft ML.NET , which allows the customization of machine learning models for use in .NET applications, either in online or offline scenarios. Allows the realization of automated forecasts when consuming the data received by the platform, through the knowledge of its standards. Based on this technology, two distinct models have been built, which aim to respond, in real-time, to the user's need to identify the activity in practice, and later, identify anomalies in the practice of the same that may mean potentially critical situations. The use of this technology over others, such as those based on the Python[29] programming language, widely applied to solve machine learning and artificial intelligence problems, arises from the easy integration in the environment developed in ASP.NET Core.

The process of creating both machine learning models is divided into two distinct steps (Figure 23). The first step, of model creation, is an iterative process that follows four distinct steps. Starts by collecting and loading the data by the application, then determines a set of operations to extract features and apply a machine learning algorithm, then trains the model with a set of data and, finally, follows the model evaluation. This process is repeated until the desired results are obtained, and consequently the choice of the algorithm with the best results, for the developed model. Finally, the model is stored for future use. After the model is created, it can be loaded to consume a new data input and return its prediction (classification) against it, using the knowledge acquired at the time of training. The next chapter is intended for a more detailed analysis of the operation and implementation decisions of the respective module.

[29] Python is an interpreted, high-level and general-purpose programming language: https://www.python.org

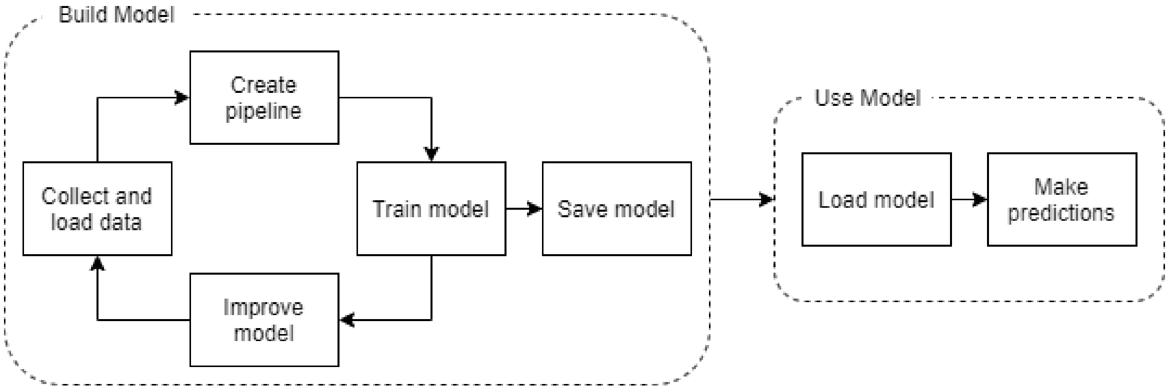

Figure 23 - Iterative process of development and use of the prediction model.

API REST

This WebService, hosted on a dedicated server, was implemented based on the ASP.NET Core 3.1 technology, in the C# development language and implements the main principles and best practices of the *RESTful* architecture. Is an independent service, which aims to serve as a middle way between the platform and other components that make it up, either feeding it with data from various sources, necessary for its operation or responding to requests for information from other customers.

As a form of request control, mechanisms of the CORS[30] *standard* were used, which aims to use additional HTTP headers to grant access to a web application running from a certain source to selected resources from a different source. A web application executes a cross-source HTTP request when requesting a resource that has a different source (domain, protocol, or port) from its own (Barth, 2011). This Webservice was implemented based on best practices and implementation *standards* of a Restful API, aiming at scalability, performance, and simplicity of use by the remaining components of the solution. Was also used management and storage caching, filtering, sorting and use of SSL certificate, as some of the measures to ensure the performance and security of the service.

The available resources differ in the power side of the ICAN(b)E platform, allowing the insertion of data from peripheral components and the support for data visualization, which presents statistical information from the analysis and interpretation of data by the ICAN(se)E module, which feeds dynamic graphics generated using the D3.js library and similar.

Provides statistical data of permanence time, by room of a certain habitation, through different time filters. By means of the request sent, the information persists in several data sources (in cloud and server), and provides processes by means of the data provided, such as the creation of a new location reading, which provides the process of classification of the activity practiced in the ICAN(se)E

[30] Cross-Origin Resource Sharing (CORS): https://developer.mozilla.org/en-US/docs/Web/HTTP/CORS

module, as well as determines the calculation of the time of permanence in the previous location, consequently updating the statistics in relation to the activity practiced previously. This service is then responsible for the depolarization of most of the analysis processes and data consumption inherent to the platform operation.

Database

For the persistence of the data coming from the ICAN(b)E aggregating platform a relational database is used in Microsoft SQL Server 2019. Is divided into two different *schemas* (page 101**Erro! Marcador não definido.**), the first being for feeding and storing data from machine learning processes applied by the ICAN(se)E module. The second, destined to store all the reading data from physical sensors in space, as well as all the data related to the space itself, users and data from the daily routine study, for history and pattern determination. Due to the exponential growth in the long term, these data lack mechanisms for standardization and subsequent storage in data warehouse tables in order to maintain the history and facilitate the application of analysis and extraction of information.

4.2.4. Client-Side

This is the layer consisting of the *frontend* application set. These components are those of interaction with the caregiver, providing the caregiver with a set of functionalities and resources, dispersed between a web application and a mobile application, described below.

WEB Aplication

The Web application gives the user access to a complete platform for monitoring and follow-up of one or more elders in their care, allowing to track their history, evolution and routine, also allowing a configuration of their preferences in relation to the behavior of the platform. Thus, this is considered the management platform, which because it is available online, it can be accessed from any browser, anywhere or device. It is possible to observe in the appendix C (Interfaces and scenarios of use), some final layouts of the applications described here.

Its development focuses on crucial aspects of web development (and not only) such as usability, user experience[31] (UX) and accessibility with the use of ARIA[32] attributes, compliance with the good

[31] The user experience (UX) portrays the emotions and attitudes of a person about the use of a particular product, system or service.

[32] Accessible Rich Internet Applications (ARIA), is a set of attributes that define ways to make web content and applications more accessible to people with disabilities: https://developer.mozilla.org/en-US/docs/Web/Accessibility/ARIA

practices established in the well-known Section 508[33] and the guidelines (WCAG 2.0[34]) that cover a wide range of recommendations to make web content more accessible.

Its design was designed according to the guidelines and standards of the Material Design[35] library, previously tested and validated by the market, to ensure good usability and better learning of the system, regardless of the technological literacy of the user. In parallel, its interface was implemented using the Bootstrap 4.5[36] framework, always maintaining its minimalist and cohesive design between the different interfaces of the platform, including the mobile application. Relies on synchronization mechanisms, of the various interface components with the data they present, allowing a constant and real-time update of the *dashboards* presented and the data consumed by the platform.

Presents vast sets of relevant information for the caregiver, such as, presentation of the indoor location in the plan of the older adult home through its position in real time, presentation of data from environmental sensors in a respective room, statistical data referring to the activity and routine with different possible filtering, presentation of the list of activities practiced and respective frequencies, as well as information from the analysis and detection of potentially critical situations such as alerts, statistics referring to detected situations, triage and feedback requests, being possible from this analysis to extract a set of data against the known pattern, from each of the activities practiced.

Mobile application - Notifier system

The notifier system consists of a mobile application, developed for the Android[37] operating system (currently the most widely used platform in the world), developed in the Java programming language. This application essentially allows the caregiver to receive real-time information regarding the state of the older adult in her/his care, and to be informed in case s/he needs to act, in a potentially critical situation.

This application shares the web application's authentication system, centralized in the Firebase Backend Authentication service, which allows the user to maintain all of her/his account settings on

[33] In 1998 Congress passed an amendment to the Rehabilitation Act requiring all websites created for the United States government to be accessible to all, despite individual disadvantages: https://www.section508.gov/

[34] Web Content Accessibility Guidelines (WCAG) 2.0: https://www.w3.org/TR/WCAG20/

[35] https://material.io/

[36] https://getbootstrap.com/

[37] Android is an operating system based on the Linux core, developed by a consortium of programmers known as the Open Handset Alliance, the main contributor being Google: https://www.android.com/

various devices and platforms. In addition to authentication, the application differs essentially in four different modules:

- **Monitoring -** Presents information that allows the caregiver to monitor the current state of the older adult in her/his care. Based on an easily interpreted visual identity, it allows the caregiver, in real time, to perceive if the state is known and normal, unknown, or is facing a potentially critical situation. Also presents data regarding her/his location and activity practiced, when known, and also global activity score, based on a set of metrics that classify, throughout the day, the performance of the older adult while staying active.
- **History -** Stores the complete set of notifications received in the application, either from the caregiver's own requests, or triggered periodically by the platform, through the caregiver's settings, or even, notifications of registration of potentially critical situations detected by the platform and results of the respective triage triggered by it.
- **Requests -** Allows the caregiver to send feedback requests, triggering on the platform mechanisms that together with the older adult, using the smart column existing in their home, pose a question and wait for a binary answer, yes or no, given the question posed. This question can be a question by default, which asks if "*Is everything ok?*", or a personalized question, inserted by the caregiver, and interpreted by the *Text to Speech* mechanism of the Android platform itself.
- **Notifications -** Both periodic notifications with statistics for a given period, and notifications relating to potentially critical situations, are presented through the application, on the caregiver's mobile device, through *push notification* mechanisms and with different degrees of severity. With the integration of the Firebase Cloud Messaging tool, it is possible to direct personalized notifications to a specific device, defining the degree of severity, which distinguishes how it is presented to the caregiver. Notifications can be triggered on the device, even if the application is not running in the background, overlapping even the remaining notifications on the same device, thus increasing its visibility.

Its implementation includes the use of the library suite that makes up the Android Jetback, together with the set of good practices implemented in it that allow greater interoperability between different versions and devices, also increasing the dynamism of information and performance, using the implementation of different mechanisms of *data binding* and navigation. The design was implemented with an identity similar to the web interface, focusing on usability and user experience, prioritizing user learning of the application. The guidelines and good practices of the Material Design library were used. Was also used auxiliary libraries that vision optimize, increase the performance and security of the application itself with is the case of Glide[38] and ProGuard[39] .

4.3.Implementation costs

As these are the predominant aspects of the conceptualized platform, and as it is implemented with low-cost IoT devices, which integrate with commercial solutions, it is essential that the total cost of implementing this platform is also reduced, and significantly lower than other existing solutions.

In this way, it will be calculated the partial cost of implementing the proposed platform, taking into consideration the minimum implementation previously determined, considering, therefore, the implementation scenario of the proof of concept of this platform. Briefly, this scenario consists of determining the location of the older adult in their own home, and when they are in the bathroom, to determine when the showering activity is practiced and the respective potentially critical situations when this activity is practiced. Thus, the following components are considered:

Table 3 - Cost of components used in the proposed platform

Component	Description	Price/unit	Quantity
Beacon iBKS 105	BLE device that periodically emits a signal, allowing the determination of the location in indoor spaces	10.45 €	5
Xiaomi Mijia 2	Environmental temperature and relative humidity sensor, which communicates by BLE	3.89 €	1
ESP32 Dev Board	Communication gateway and data collection between IoT devices and server	3.68 €	2
Google Home Mini	Smart column, for interaction with voice interface	39.90 €	1

As it can be seen (Table 3), the implementation of the proposal had a cost of approximately 100 euros, and in this scenario, it is contemplated the implementation of beacons devices in all rooms of the housing, as well as the smart column, which in principle will be enough one per housing (depending on the area of the same), making these more than 90% of the cost of implementation. Thus, when considering a more complete implementation, which involves more action scenarios, it

[38] Glide is a fast and efficient image loading library for Android focused on smooth glide: http://bumptech.github.io/glide/

[39] https://www.guardsquare.com/en/products/proguard

will be enough to add only a few components (sensors) of low cost, for data collection, not increasing significantly the total cost of the platform.

Should be noted that for the calculation of the total cost of the platform, the costs related to the internet and peripherals, such as routers, mobile devices, computers, among others, were not taken into account, considering that they belong to the user.

Is essential to consider that this implementation was carried out with commercial equipment, developed by third parties for various purposes and capacity for integration with existing platforms in the market. When customizable and developed for a specific purpose, this type of component can have a drastically lower cost per unit. Another factor is the number of devices purchased, which in larger numbers, will significantly lower the cost of them. The *beacon* devices used in this platform, although they can be used as final devices, are devices in the development range, providing the device with a higher number of resources, but that makes the final solution more expensive, like the gateways used. In the near future, with the creation of specific *hardware* for the scope of implementation, such as a *smart band weareable* as a gateway, custom *smart speaker*, as well as the *beacon* devices themselves and other sensors, the platform may have a much lower final cost of implementation.

5

ICAN(se)E – Trace and Monitoring

This is the central module of the developed platform. Consists of the application of analysis and data mining techniques, information extraction and machine learning, to assign an expression to the values and data collected by the platform, converting into meaningful information for the caregiver and the safety of the older adult.

The monitoring process is composed of two distinct stages: classification of the human activity practiced in real-time, and anomaly detection (possible critical situations) during this activity (see Figure 24). Each stage requires a distinct approach and analysis through its features and scope. Is the culmination of both stages that allows adding an analytical component with expression to the platform developed, to contribute to its goal of prevention and support to the safety and well-being of the older adults in their daily routine, and consequently to support the role of the caregiver in its monitoring and intervention.

A concrete activity will be analyzed, with expression at the level of criticality in the daily routine of the older adult, as proof of concept for the models and algorithms developed to support data classification. Typically, in most bathrooms, when taking a bath or shower, two of the most significant changes at the environmental level are the significant increase in temperature and relative humidity in the room. These conditions can, indeed, be influenced by several factors such as space heating, the existence of windows and air extraction, volume of air renewed in the room throughout the activity, among others. However, changes are always perceptible, and it is possible to determine a pattern when the analysis focuses on the same activity, executed by the same person in the same space. In order to show that there are two features (identified a priori as being susceptible to modification), other features can be calculated, to show changes or tendencies of modification, in comparison to the moment under analysis.

Once the mentioned activity is determined with some certainty, the process of anomaly detection begins. It is known, based on the data collected, that on average an older adult in the shower activity has a duration of about nine minutes. While another distinct activity is not detected, one of the collected features by the platform is the current duration of the activity. The average duration may change, but if after fourteen minutes (time equivalent to the average time of the activity plus a 50% variance), it is still verified that the older adult still performs the same activity, the deviation to the usual value starts to be quite accentuated, revealing to be an atypical situation. At this moment, triage mechanisms should be automatically triggered to validate the possibility of a potentially critical situation.

This entire analysis process follows a model of knowledge extraction and machine learning. The process of data analysis performed over time recalculates the known metrics and adjusts the known patterns for each activity execution for each user. This step is fundamental to increase the precision achieved.

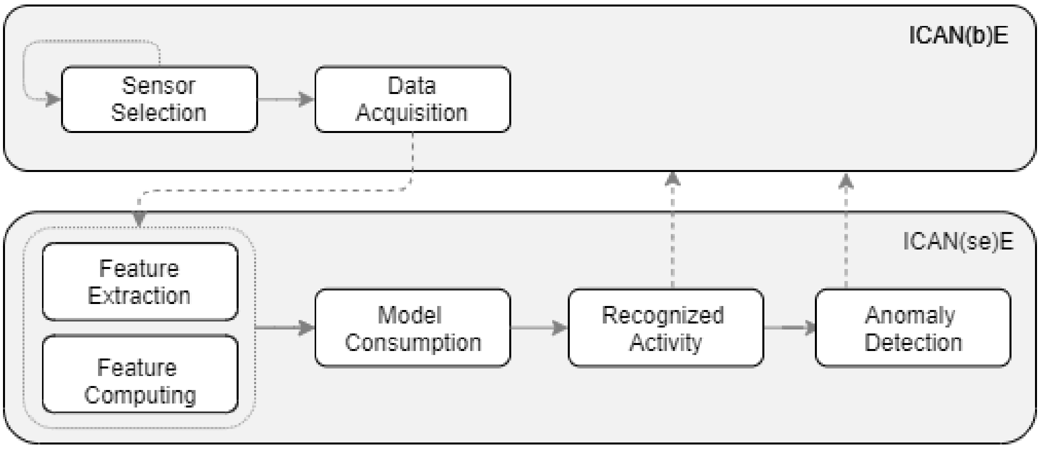

Figure 24 - Process sequence of module ICAN(se)E

The data model represented (see Figure 25) supports the machine learning process: classification and prediction of the platform, establishing a relationship with the information of the entire system. Focuses on the task of classifying human activity performed by an older adult in the context of their home, and consequently analyzing possible critical situations, defined as anomalies, to the known pattern.

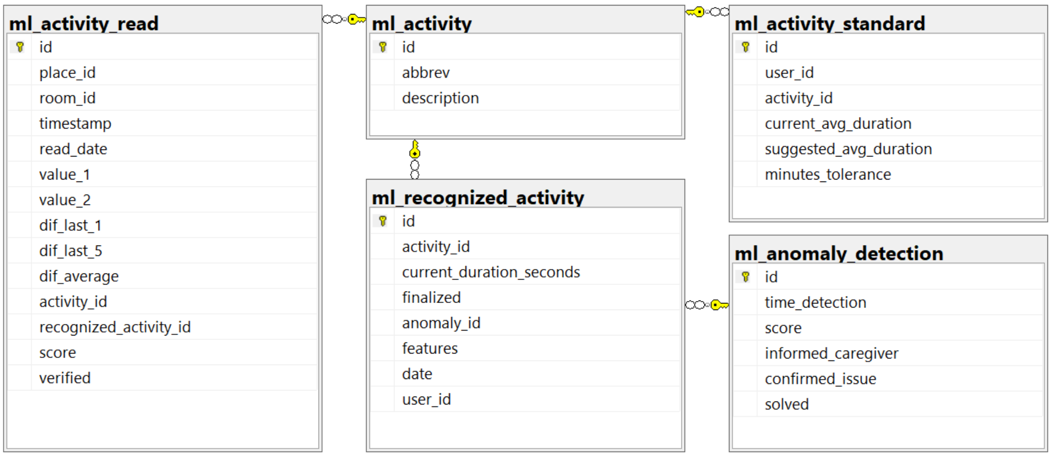

Figure 25 - List of the subset of tables supporting the information extraction module

The following table (Table 4) presents a brief description of the relational model' entities to support the triage and activity monitoring module:

Table 4 - Description of the set of tables of the machine learning platform

Table	Description
ml_activity	Identifies a known and parameterized activity on the platform.
ml_activity_standard	Known defaults of the practice of a certain activity, by a specific user. The data in this table may be adjusted based on the readings and respective classifications made by the machine learning mechanisms.
ml_activity_read	Complete and transversal reading of a set of features, following a *Data Warehouse* approach, in the sense that it concatenates and centralizes a set of existing significant information dispersed by the relational model, thus providing the classifier with the necessary information so that it can classify, with the greatest possible accuracy, an activity known by the platform. Through the type of elaboration obtained, a set of characteristics is extracted, with the application of a mathematical model, in order to support the process of training and prediction of the classifier. The implemented classifier is based on multiclass classification algorithms, allowing the distinction between more than two classes (unlike binary classification). Once classified as a known activity, an entry is inserted in the table *ml_recognized_activity*, in order to proceed to the detection and classification of anomalies to the activity pattern. The classified and validated readings, that is, which classifier was able to successfully determine the activity practiced, serves as a training model for the machine learning process.
ml_recognized_activity	Features associated with a previously classified activity, which will serve as a basis for abnormal activity detection, by a certain monitored user, in order to detect potentially critical situations.
ml_anomaly_detection	Identifies a potentially critical situation, which should be validated with the caregiver.

5.1. Recognition of human activity as a multiclass classification problem

The process of recognition of the activity practiced, by each of the older adult monitored by the platform, in their own home, consists of a continuous triage process, based on the application of supervised classification algorithms.

The insertion in the table *ml_activivity_readings* is triggered by an event, such as the detection that the older adult moved to another division. At this moment, it is known that a distinct activity is taking place, and the known data set must be agglomerated in a table that centralizes information. Data is collected from each house division in which the older adult is, with a constant periodicity. In these data there is information about the older adult, her/his location, and environmental values of the division in which s/he is located. From this moment on, there is the necessary information to make a correspondence with known activity, from the pattern that the data presents.

To establish the pattern under analysis, it is necessary to determine the most relevant features to it. The more discriminative the chosen features are, the higher the effectiveness. However, there is no recipe for their choice, and they must be well considered. Knowing that the more features are provided, greater may the computational effort be. However, the lack of those features may increase the error. Therefore, features should be collected through the process of selecting a subset of the original features or extracted through the definition of new features that can be functions of the originals. The purpose of selecting the features is to find the best subset, of dimension *d*, of the full set of features, with dimension *D*. Has as criteria, the minimization of the error, being the best solution detected only after the exhaustive search in all the possible sets. In practice, this is impracticable unless heuristics are used. The objective of extracting features is the application of types of transformations on the original set of features so that the classes are more separated, simplifying the selection problem.

After selection, it is possible to generate a prediction model, which applies a set of supervised classification algorithms, which work based on knowledge. To achieve success, an effective model training process is required, with a significant set of previously classified data, to expand its knowledge base.

When a new data entry is received, this model will be used to predict the activity performed. This process works based on a probabilistic model, where it is determined with a certain probability, the possibility that the set of data provided represents the practice of a specific activity. When a known activity previously parameterized in the platform is determined, a new entry in *ml_recognized_activity* is inserted, starting the process of detecting anomalies to the current activity.

5.1.1. Problem analysis and extraction of characteristics

The feature selection process is one of the most important steps in developing a solution based on information extraction. Features must be relevant and express significantly different values to express a certain pattern for a specific activity. For the problem under analysis, a set of features will be extracted, received directly from the location and environmental sensors existing in the house. With these, a correlation in which it is identified that for a certain user can be established, in a certain division, when certain values from the existing sensors in the space are obtained, representing a certain activity.

To facilitate this process, some features are calculated by the platform, from the collected data, to increase the amplitude of the analysis performed, thus comparing the received data with the already known data. This step allows us to deduce the set of features that give a greater expression to the analyzed data, contributing to a more unequivocal classification.

The first calculated feature aims to understand the evolution of both values received from the sensors reading. Thus, the mean is obtained, from the sum of the difference, of the two characteristics (represented by *Cn*) under analysis, for the two last readings obtained:

$$difference\ from\ the\ first = \frac{(C1_{atual} - C1_{atual-1}) + (C2_{atual} - C2_{atual-1})}{2} \tag{5.1}$$

Following the calculation of the previous feature, the following calculated feature aims to quantify the change occurred in the reading of the values obtained, based on the last five readings performed, thus transmitting a perception regarding the tendency of growth of the values obtained:

$$difference\ from\ last\ 5 = \frac{\sum_{i=1}^{5}(C1_{atual} - C1_{atual-i}) + \sum_{i=1}^{5}(C2_{atual} - C2_{atual-i})}{5} \tag{5.2}$$

Both formulas are based on the progressive evolution of the last readings performed. For this purpose, and with equal weight in the feature calculation, the median value (see 5.3) of the two features previously calculated, the last reading immediately before and the last five readings in a row (if any) are taken into account. Is, thus, possible to assess whether the tendency is for negative or positive growth, as well as whether it is still present in the immediate future.

$$average\ difference = \frac{difference\ of\ last +\ difference\ of\ last\ 5}{2} \tag{5.3}$$

With this last stage it is obtained a feature that allows us to arrive at a rational number (Q). The absolute value (or module) identifies the slope of the growth, the higher, the more pronounced. The sign, in turn, identifies the tendency of the growth verified, which can be positive (increasing) or negative (decreasing).

In order to do so, the difference between the current reading value of each feature is added together with the last five readings of the same feature, adding both features in analysis and calculating the average value. In this way, the evolution of the readings taken is perceived.

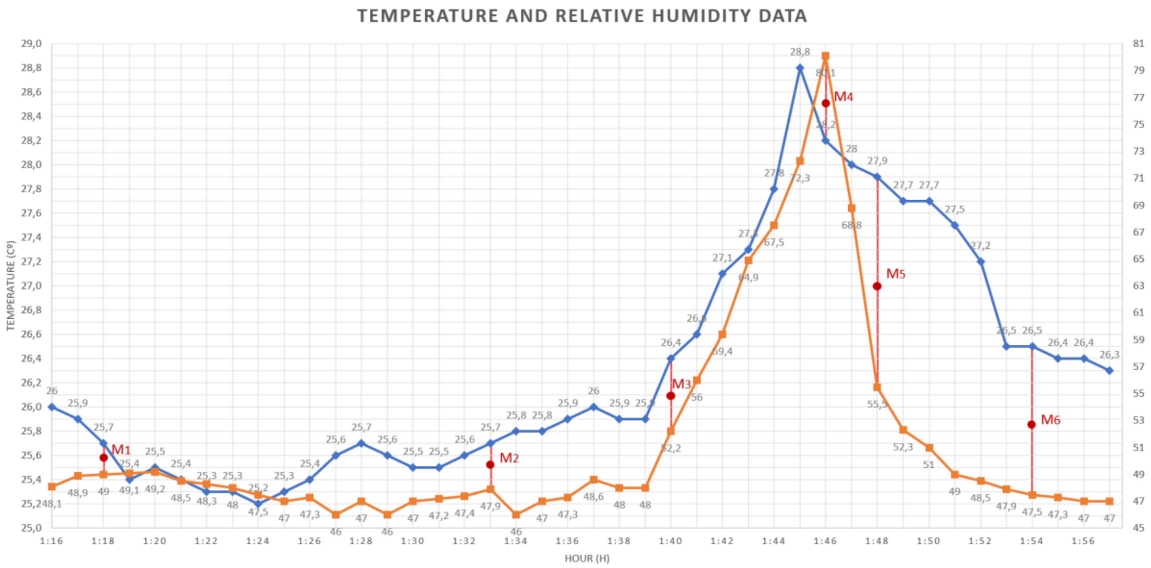

Figure 26 - Features extraction analysis chart for the reading of temperature (blue) and relative humidity (red) values of a user's shower activity.

The graphic represented in Figure 26 shows the values corresponding to the collection of data from environmental sensors, assembled in the bathroom of a platform user when practicing her/his daily shower activity. It is possible, through this, to analyze a set of extracted characteristics, represented in Table 5, as well as analyze six distinct moments, selected based on the variation of the temperature-relative humidity combination, being this choice, for the majority, based on the variation of the underlying characteristics, that present significant results for the analysis and classification process of the shower activity.

Table 5 - Set of features obtained for the moments under analysis from the values obtained, when performing the shower activity of a platform user.

	Obtained Values			Calculated Values			Analysis	
Moment	Hour	Value 1	Value 2	Dif. 1	Dif. 5	Avg. dif.	Growth	Description
M1	**01:18**	**25,7**	**49,0**	**-0,05**	**n/a**	**-0,05**	**Not significant**	**The user is in the space, without taking a shower.**
M2	**01:33**	**25,7**	**47,9**	**0,30**	**1,10**	**0,85**	**Not significant**	**The user is in the space, without taking a shower.**
M3	**01:40**	**26,4**	**52,2**	**2,35**	**4,92**	**4,81**	**Positive (+)**	**Moment at which the user takes a shower.**
M4	**01:46**	**28,2**	**80,1**	**3,60**	**16,76**	**11,98**	**Positive (+)**	**Moment at which the user takes a shower.**
M5	**01:48**	**27,9**	**55,5**	**-6,70**	**-15,34**	**-14,37**	**Negative (-)**	**The user is in the space, without taking a shower.**
M6	**01:54**	**26,5**	**47,5**	**-0,20**	**-3,06**	**-1,73**	**Not significant**	**The user is in the space, without taking a shower.**

Based on the environmental values, a set of features were calculated as described. In a more careful analysis of the values obtained, sketched in the form of a graph, it is possible to empirically determine the moment of the shower activity practice. By relating the observations with the calculated values, it can be understood that the growth tendency (positive or negative), has a direct relation with the practice of the activity under analysis. In this case, when values with expressive positive growth are obtained, it means the practice of an activity. The significant decrease of these values, later, indicates the end of the practiced activity.

In this way, and based on the analysis of the graphic and values obtained from the extracted and calculated characteristics, is is possible to determine with some degree of reliability, that the user practiced the shower activity between 01h40 and 01h46, with a duration of approximately 6 minutes. Is also possible to deduce the existence of a pattern, relative to the values obtained, concerning the accomplishment of this activity by this user.

5.1.2.Training set and algorithms

One of the fundamental steps in the creation of the estimation model is the process of training the classifier. In this case, a supervised model is used, so the expected results, coming from the classified data of the training set, are identified and known a priori (see Figure 27).

The process is divided into two main steps, where the training data set is subdivided, typically in the proportion 80-20. The data set used must have a significant volume to obtain expressive results. The first subset (80%) is used to feed the classification algorithms. The remaining volume of data (20%) is used to evaluate the assertiveness of the algorithm used, comparing the estimated result with the known result. Normally, in the training process, a set of classification algorithms of one or more families is used, with specific heuristics, to identify which one obtains the best performance and will be used in the model for future predictions.

This process should be repeated over time until the data set becomes robust enough. This step is necessary to obtain an adjustment of the model in order to be able to change its specificities.

The training data set used to create the multi-class classification model was automatically created through data collected by the platform, classified later through a manual process.

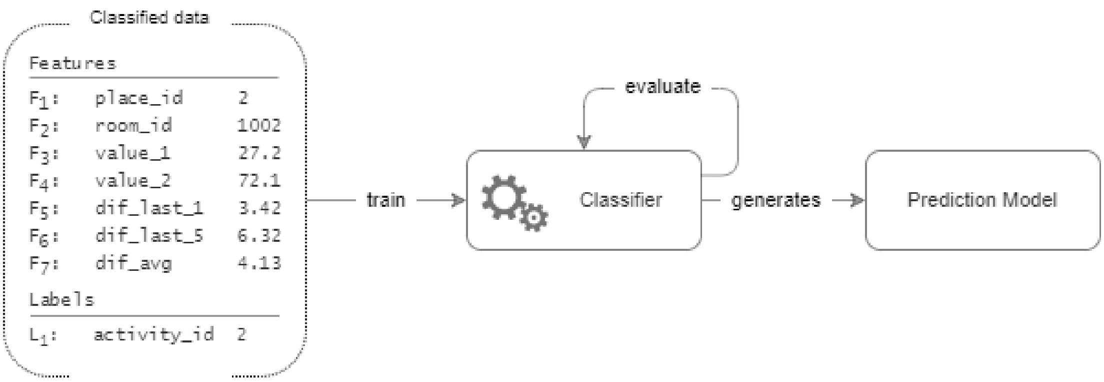

Figure 27 - Classifier training process and prediction model generation.

5.1.3. Model evaluation

Evaluation is the process of measuring the quality of the model. There is a specific set of evaluation metrics to be considered, through the type of machine learning task that the model performs. The most common set of metrics for a multiclass classification model, which aims to measure the accuracy of the predicted category, against the actual category, follows (see Table 6).

Table 6 - Evaluation Metrics for Multiclass Classification

Metrics	Description	Objective
Micro-Accuracy	Aggregates the contribution of all classes for the calculation of the average metric. Is the fraction of instances correctly predicted. The micro-measure does not take into account the relationship with the class. Each pair of sample classes also contributes to the precision metric.	**The closer to 1, the better.** In a multiclass classification task, Micro-Accuracy is preferable to Macro-Accuracy if you suspect that there may be class imbalance (i.e., you may have many more examples of one class than of other classes).
Macro-Accuracy	The accuracy for each class is calculated and the Macro-Accuracy is the average of these accuracies. Each class also contributes to the accuracy metric. The minority classes have the same weight as the classes in greater numbers, regardless of the number of instances of that class the data set contains.	**The closer to 1, the better.** Calculates the metric independently for each class and then considers the average (thus treating all classes equally).
Logarithmic Loss	Logarithmic loss measures the performance of a rating model where the input prediction is a probability value between 0.0 and 1.0. The logarithmic loss increases as the predicted probability deviate from the actual label.	**The closer to 0, the better.** The goal is to minimize the value obtained.
Logarithmic Loss Reduction	The logarithm loss reduction can be interpreted as the advantage of the classifier over a random prediction.	**Varies between -infinite and 1, where 1 is perfect predictions and 0 indicates average predictions.** For example, if the value is equal to 0.3, it can be interpreted as "the probability of a correct rating is 30% better than a random rating".

In the context of the problem, the most relevant metric for multiclass classification is the micro precision, in order to compensate eventual unbalances in class classification. The closer the micro accuracy of 100% or 1, the better. Another important metric for the multiclass rating is macro-accuracy, which like micro-accuracy, the closer to 1 the better.

The macro accuracy method can be used when you want to know how the system works globally in all data sets, however, it should not be made any specific decision using this indicator.

In the implementation of the multiclass classification model, the use of the training algorithm called *AveragedPerceptronOva* was determined, because although the micro and macro accuracy value was identical among all those tested (≈0.983) the performance was slightly better in this case (53.2 seconds for a data set around five thousand entries). The perceptron is a classification algorithm, introduced by F. Rosenblatt in 1958 (Rosenblatt, 1958), that makes its predictions by finding a hyperplane separator. For example, with characteristic values $f_0, f_1, \ldots, f_{D-1,}$ the forecast and given determining on which side of the hyperplane the point is located. This is the same as the sign of the weighted sum of the characteristics, that is:

$$\sum_{i=0}^{D-1}(\boldsymbol{w_i} * \boldsymbol{f_i}) + \boldsymbol{b} \quad (5.4)$$

Where $w_0, w_1, \ldots, w_{D-1}$ are the weights calculated by the algorithm, and *b* and *bias* learned by the algorithm.

Perceptron is an online algorithm, which means it processes the inputs of the training set, one at a time. Starts with a set of initial weights (zero, random, or initialized from a previous apprentice). Then, for each example in the training set, the weighted sum of the characteristics is calculated. If this value has the same sign as the label of the current example, the weights remain the same. If they have opposite signs, the vector of weights is updated by adding or subtracting (if the label is positive or negative, respectively) the vector of characteristics of the current example, multiplied by a fact $0 < a \leq 1$, called learning rate. In a generalization of this algorithm, the weights are updated by adding the characteristic vector multiplied by the learning rate, and by the gradient of some loss function.

In the case of the *average perception*, for each iteration, i.e. passing through the training data, a weight vector is calculated as explained above. The final prediction is then calculated by calculating the weighted average sum of each weight vector and looking at the resulting signal.

The algorithm used is derived from the *OneVersusAll* (OVA) family of algorithms. In this strategy, a binary classification algorithm is used to train a classifier for each class, which distinguishes this class from all other classes. The prediction is then executed by executing these binary classifiers and choosing the prediction with the highest confidence score.

5.1.4. The use of the prediction model

The process of classification of the activity practiced by the older adult, in real-time, is a continuous process and is triggered in several different moments, which can be:

- When the change in the division is detected. As a rule, whenever there is a displacement between rooms in the house, the end and/or beginning of a new activity is assumed. This is a key moment to determine the activity, based on the values collected from the physical space;
- Until a specific activity is determined, with a higher temporal periodicity, so that it is determined more quickly, continuing with the remaining monitoring process;
- When a specific activity is determined, this time with a lower periodicity. Is important, although the activity practiced at the moment is determined, to notice the moment when it ends. At this moment the normal classification begins, but also the process underlying the monitoring of the previously determined activity, whose objective would be to determine the normal course of the same, ends.

Once the precision model has been trained, it can be used for the classification process - assigning a concrete class to the set of values received. The model then receives the input of a set of features extracted, from the previous reading, where with the application of a classification algorithm it will determine, with a certain degree of certainty, to which class it belongs. Finally, it returns the result of the prediction made, with the respective probabilistic values of assignment, to each of the known classes (see Figure 28). The closer a certain classification value is to 1, the greater the probability that it belongs to that respective class. Since the use of supervised classification algorithms is involved, the training process is fundamental to achieve success in this predictive process. To increase classification performance, this process must be based on a significant and varied set of training.

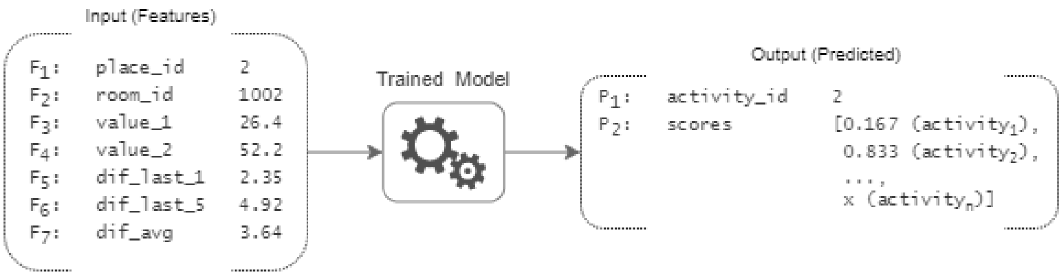

Figure 28 - Multiclass classification process: data input and output.

After the determination of the practice of a specific activity, the second predictive process begins, to detect anomalies to its practice.

5.2. Anomalies Detection: detecting anomalies to the pattern of the activity practiced

The objective of this module is to perceive potentially critical situations, from the data consumed by the platform. This process consists of the analysis and detection of abnormal data to the known standard or tendency, within the same context. By definition, anomalies are rare events, so it can be difficult to collect a representative sample of the data to be used for modeling. The data sets used are usually unbalanced, something that adds a major challenge in the model design and training process.

The detection of anomalies signals unexpected or unusual events or behavior. Gives clues about where to look for problems and helps to answer if a certain reading may be inconsistent with others. In the context of the problem under analysis, this step follows after the classification of the activity practiced by the older adult at the moment. There is a certain pattern to the practice of a certain activity, such as, for example, the average time it takes to perform it.

Considering the activity under analysis, the daily shower, the challenge is to try to understand, during the action, if it extends over a period significantly longer than the normal practiced by that user. If this happens, it may be a potentially critical situation, which needs some kind of analysis and/or triage. In this case, it may be a situation of fall or indisposition of the older adult, when practicing this activity.

5.2.1.Temporal series anomaly detection

The anomaly detection process aims to signal unexpected or unusual events or behaviors. Gives clues on where to look for problems and helps to understand if a given sample is unfamiliar, given the problem under analysis. This approach is often used in search, failure detection and critical situations in real time, however, it can also be used to detect situations of error in the past, which have derived in consequences or even to relate behaviors (effect-cause).

Normally, there are two ways of performing the analysis of anomaly detection in time series:

- The **peaks**, which indicate a temporary and anomalous growth of certain behavior in the system.
- The **points of change**, which indicate the beginning of changes with a longer or permanent duration, in the behavior of the system.

5.2.2.Peak detection

This is the most relevant analysis for the detection of potentially critical situations, according to the case study. The objective of peak detection is to identify sudden but temporary anomalies that differ significantly from most time-series data values. Is important to detect these rare events, or observations, promptly to be minimized.

The following graphic (see Figure 29) shows, through the data collected by the platform, a time series of twenty days, the duration of the daily shower activity of a specific user. Is easy to notice the existence of a tendency in the duration of this activity, and in turn determine an average duration, for it, of about 7 minutes and 35 seconds. Is also noticeable, the existence of an atypical event, day 11, with the duration of 22 minutes, being this a very significant deviation to the known pattern, of the practice of the activity by this user. This, of course, is an alert situation, of potential risk, so the platform, when detecting, triggers all the necessary triage and warning mechanisms.

Is worth mentioning that these mechanisms were triggered around 14 minutes and 30 seconds (marked by the red line), when the platform classified the practice time of the activity, as anomalous.

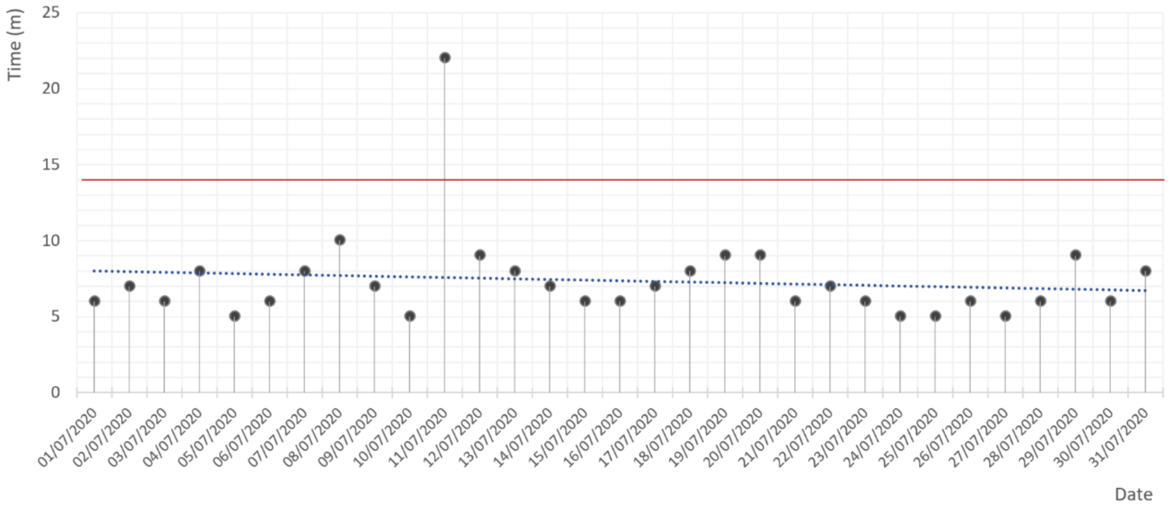

Figure 29 - Analysis of the duration of daily shower activity of a certain older adult and detection of abnormal values.

5.2.3.Detection of change points

This analysis has a greater expression for the detection of changes to the pattern, of a permanent nature, and can serve for the adjustment of metrics and the known pattern of a certain activity practiced, by a specific user. This process is fundamental for the correct follow-up of the user's habits and consequently, the subsequent detection of sudden changes in her/his routine.

On the other hand, it is also an essential analysis to perceive momentary changes in the individual's behavior, which may indicate risk factors. In the following study case, the graphic (Figure 30) that expresses, through the readings made by the platform, the total time that an older adult remained in a certain room can be analyzed. In this case, after the perception of a significant alteration to the known pattern, as well as in the average time spent by this user, in this same division, it is perceived to be an unusual increase. Looking at the graphic, the period in which this change appeared can be identified, as well as the moment in which values return to approximate values of the known pattern, where the average daily stay in this division by this user, is around 411 minutes. This change, detected by the platform and communicated to the caregiver, allowed him/her to interact with the older adult to understand the situation.

This type of analysis allows the perception of important situations without prior information on the part of the older adult, or even situations that would not otherwise be perceived. The aim is to provide the caregiver with a set of analysis tools to be able to intervene actively, even if s/he or she is not able to make a constant follow-up *in situ*.

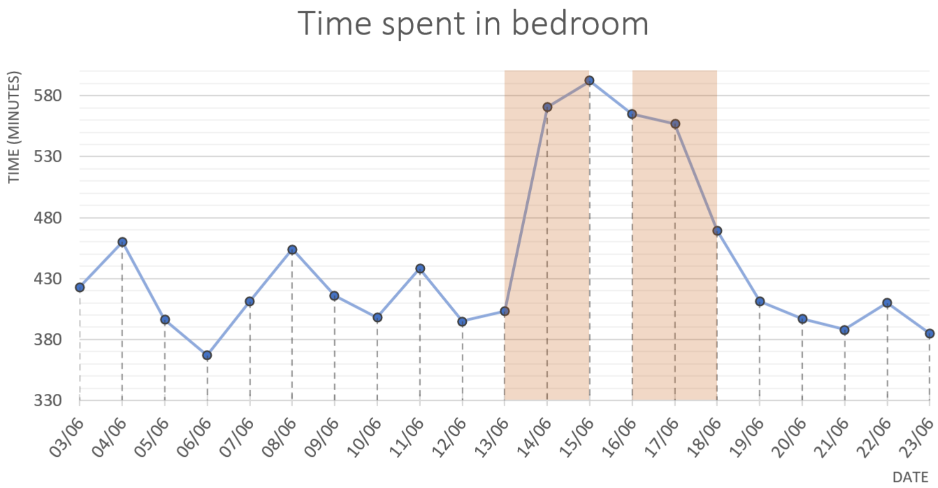

Figure 30 - Average of daily minutes spent in the room (room) by a specific user during the period of 20 days.

5.2.4.Model evaluation

Similar to previous predictions, the training process is fundamental to provide the model with information that will allow it to handle and classify new data entries, different from the others already analyzed. To train the model, a data set previously created and provided with the cases of anomalies identified is used, to serve as a standard for the training algorithm of the estimator model. After the training process, the evaluation of the model is started to determine with which algorithm and heuristics a better performance is obtained in face of the problem in question.

The following (see Table 7) are some of the metrics usually considered for performance evaluation, the use of algorithms focused on analysis and detection of anomalies in time series (Gaur et al., 2019).

Table 7 - Evaluation Metrics for Anomaly Detection

Metrics	Description	Objective
Area under the ROC curve	The area under the receiver operator curve measures how well the model separates the usual and anomalous data points.	**The values closest to 1 are better.** Only values higher than 0.5 demonstrate the effectiveness of the model. Values equal to or less than 0.5 indicate that the model is no better than randomly allocating inputs to anomalous and usual categories.
True Positive Rate (TPR)	Is the proportion of correctly identified positive classes from the total possible positive conditions, that are true positives (TP) and false negatives (FN). In the context of anomaly detection, TPR measures the fraction of anomalous events identified by a given method.	**The values closest to 1 are better.** If there are no false negatives, then this value is 1.
False Positive Rate (FPR)	The detection rate with false positive count is the ratio between the number of correctly identified anomalies and the total number of anomalies in a set of tests. That is, there is a value for the detection rate in the false positive count.	**The values closest to 0 are better.** If there are no false positives, then this value is 0. Refers to the rate of false alarms or fall-out.
True Negative Rate (TNR)	Is the proportion of correctly identified negative classes from the total possible negative conditions, that are true negative (TN) and false positive (FP).	**The value closest to 1 are better.** In the context of anomaly detection, TNR measures the fraction of non anomalous events.

The estimator chosen for the pattern prediction model is known as *SsaSpikeEstimator* , which predicts peaks in time series using *Singular Spectrum Analysis (SSA)*. SSA is a powerful framework for decomposing time series into trend, seasonality and noise components, as well as for predicting future time series values (Golyandina & Korobeynikov, 2014).

This estimator receives a single parameter, with a value corresponding to a chronological moment, and will return a vector composed of the alert level (value other than zero means a point of change or an anomalous value), assigned score, and *p-value*. Once the raw score for a chronological point is calculated, the anomaly marker component is fed to calculate the final anomaly score for that chronological point. The *p-value* score indicates whether the current point is an *outlier* (also known as a peak). The lower its value, the more likely it is that it is a peak, and its value is always between [0, 1]. The calculation of this value for each point in time is the *p-value* of the current raw score, calculated according to a distribution of the raw scores. If the *p-value* exceeds $1 - \frac{confidence}{100}$, this point in time gets an alert value other than zero, so it means detecting a peak. The confidence value is presented in the range of [0, 100] and determined by the internal implementation of the algorithm.

Is presented in appendix (page 102) the result obtained from the training process of the implemented prediction model, where the correct detection of a point of anomaly is notorious, in relation to the time series. This set of training data was collected on-site by the platform itself and is relative to the duration of the daily shower activity of an individual. The anomalous value could mean a situation of potential risk.

5.3.Analysis and Evaluation

This topic presents the evaluation tests performed on the developed system and the respective results obtained. They focus essentially on the classification models and the respective information extraction process, from the data consumed by the platform.

5.3.1.Proof of concept and tests

Given the pandemic situation and the respective need to prevent and contain the SARS-CoV-2 virus, which causes the COVID-19 disease, the performance of final tests in a real context of use with its end users was thus impossible, until the end of this dissertation. Thus, and given the reality of confinement, as a proof of concept, the implementation was replicated and used in daily life, in my own home. This way, although not with the end-users, it was possible to validate a whole set of results, coming from the platform's actions, in face of my daily activities.

The proof of concept follows the basic experiment, already introduced in previous chapters. Each room is equipped with beacon devices, in order to determine the user's internal location, as well as her/his physical context. Scattered, per room, are sensors of temperature and relative humidity, to determine the practice of some potentially critical activities, such as showering, in the bathroom.

5.3.2.Results Evaluation

The platform must be evaluated as a whole, considering the integration of all its components. Functionalities, performance, and usability have to be validated. Each component must also be tested and validated on an individual basis.

Regarding the machine learning component, according to the sensitivity of the data from this process, it is required to evaluate extensively the classification accuracy of the developed models, using a specific set of metrics. The evaluation comprises several aspects regarding the model creation, the training process, and the classification values obtained using it.

5.3.3. Training Results

The training process, and the consequent determination of the algorithms to be applied, are a fundamental step in structuring a *machine learning* solution. The determination of the practiced activity is a problem of multiclass classification, being for this evaluated a set of 4 algorithms that usually have a good performance in the resolution of this type of problem. The evaluation metrics selected to determine the best model are in this case: (i) the execution time of the algorithm duration; (ii) the macro-precision that calculates the metric independently for each algorithm and then obtains the average; and (iii) the micro-precision that aggregates the contributions of all the algorithms to calculate the average. From the set evaluation, the use of the *AveragedPerceptronOva* algorithm is determined by the performance achieved, according to the following table:

Table 8 - Experimental results of the multiclass classification model - 15 seconds and data set with 400 entries.

Algorithm	Micro-precision	Macro-precision	Duration
AveragedPerceptronOva	1.0000	1.0000	2.2
SdcaMaximumEntropyMulti	1.0000	1.0000	3.4
LightGbmMulti	0. 9286	0.9375	2.6
SymbolicSgdLogisticRegressionOva	0.2308	0.2500	2.2

In a multiclass classification task, micro-precision is preferable to macro-precision if suspected that there may be an imbalance between the entries corresponding to each class. Thus, this was the metric with the greatest weight for the choice of algorithm, together with its execution time. A data set, with 400 previously classified inputs, was used, and the model was trained for 15 seconds (see Table 8).

After the training process, it is necessary to proceed to the validation of the results to determine the assertiveness of the model and adjust the necessary parameters to optimize its estimation. Cross-validation is a technique to evaluate the generalization ability of a model from a data set. This technique is widely used in problems where the objective of modeling is prediction. The aim is to estimate how accurate this model is in practice, that is, its performance for a new data set. The central concept of the cross-validation techniques is the partitioning of the data set into mutually exclusive subsets, and then the use of some of these subsets for the estimation of the parameters of the model (training data), the remaining subsets (validation or test data) being used for the validation of the model. In this case, a convention called the holdout method was used, which consists precisely in the distribution of the data set into training and validation subsets, in this specific implementation in the proportion of 80/20%, respectively. From the process of validation of the multiclass classification model, the Table 9 is obtained:

Table 9 - Cross validation to obtain the model accuracy metrics

Metrics	**Value**	**Standard Deviation**	**Confidence Interval 95%**
Micro-Accuracy average	0.975	0.056	0.055
Macro-Accuracy average	0.967	0.075	0.073
Logarithmic Loss average	0.108	0.098	0.096

The results, both for micro and macro-precision, are, as better as they approach the value 1. The logarithmic loss, on the other hand, acts as penalizing the false classifications. Works well for multiclass classification. The classifier must assign a probability to each class for all samples. The log loss value, the closer is to 0, the more precise is the classification. Suppose N samples are belonging to the M classes, then the log loss is calculated as below:

$$Logarithmic\ Loss\ = \frac{-1}{N}\sum_{i=1}^{N}\sum_{j=i}^{M} y_{ij} * \log(p_{ij}) \tag{6.1}$$

Where:

y_{ij} = indicates whether sample i belongs to class j or not

p_{ij} = indicates the probability of sample i belonging to class j

Based on the values obtained (Table 9), it is possible to conclude that the results are quite satisfactory.

5.3.4. Classification Results

The model was evaluated using several important metrics, including precision, recall, F_1-scores, and accuracy. All these metrics represent the rate of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), representing them in various ways:

$$Precision = \frac{TP}{TP + FP} \tag{6.2}$$

$$Recall = \frac{TP}{2TP + FN} \tag{6.3}$$

$$F_1 score = \frac{2TP}{2TP + FP + FN} \tag{6.4}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6.5}$$

Where:

TP = True Positive (the cases where YES is predicted and the actual result was also YES)

FP = False Positive (the cases where YES is predicted and the actual result was NO)

FN = False Negative (the cases where NO is predicted and the actual result was YES)

TN = True Negative (the cases where NO is predicted and the actual result was NO)

Precision is also known as a positive predictive value, whereas recall is also known as sensitivity. From the above equations, as the number of false negatives and false positives approaches zero, all of the scores approach one. So, a perfect classifier will achieve a score of one for all the above metrics. The recall for a class is the number of items correctly predicted as belonging to that class divided by the total number of items that belong to the class. F_1 score is the weighted average of Precision and Recall, therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F_1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy is the number of correctly classified items divided by the total number of items in the test set. Ranges from 0 (least accurate) to 1 (most accurate). Accuracy is one of the evaluation metrics of model performance. Should be considered in conjunction with precision, recall, and F_1 score.

By evaluating the classification data from the classifier created, after training of the same, for a total of 100 classifications, related to the problem of identifying the showering activity, the following confusion matrix is obtained:

Table 10 - Confusion matrix for classification of daily shower activity class

		Actual Value	
		positives	negatives
Predicted Value	positives	TP 18	FP 0
	negatives	FN 0	TN 82

This concrete case is quite simple to understand. The classifiers only must determine between the shower activity or other unknown. The data obtained were directly received by the platform, from the existing sensors in the bathroom. From the analysis of Table 10 is clear that *accuracy's* result compared to the data obtained was 100%. Consequently, the value of 1 for *precision*, *recall* and *F-score* were obtained, simultaneously. Another important aspect is the fact that from the classification model, each class was correctly classified, always with a degree of certainty never lower than 75%.

Although the simplicity of the problem does not allow the success obtained in different contexts to be lost, it is concluded that it is a very positive basis.

6

Conclusions and Future Work

This chapter presents general conclusions about the work developed, as well as solutions and ideas for future work that expand the contributions presented in this dissertation.

6.1.Synthesis and Accomplished Objectives

Different studies were carried out, with different degrees of maturity to evaluate not only the various components of the platform, but also as a whole, which proved to be fundamental for a continuous improvement of the final solution.

The technological platform implemented, manages at this moment to respond to a set of real-world problems, related to the permanence of the senior in their home, without continuous monitoring. This platform can accurately determine potentially critical situations in daily activity, such as showering, where when an anomaly is detected, it can trigger triage mechanisms with the senior and notify their caregiver. Also allows the user, when facing a critical situation or disability, using voice interaction, to trigger a request for help with their caregiver. The use of the mobile application by the caregiver not only allows real-time monitoring of the older adult in her/his care but also when considered relevant, to request feedback regarding the older adult’s condition. The platform is equipped with intelligent mechanisms for information extraction, capable of determining patterns related to the older adult's daily activity in her/his home, gauging metrics related to each of the activities executed, and used afterwards to determine anomalies to the performance of a particular activity. The statistical analysis from the data treatment also provides the caregiver with a powerful tool for the interpretation of possible indicators of changes in the health status of the older adult, both momentarily and in the long term, highlighting situations, such as the loss of physical-motor capabilities, cognitive or depressive episodes.

The development of this research work brought added value to society with the design and implementation of a platform responding to well-known societal challenges. Additionally, it was also possible to respond to the three research questions formulated at the beginning of this dissertation.

- The first, Q_A ("*Using the existing devices and technology, is it possible to design a platform, to provide to the caregiver a set of tools that facilitates their task of supporting the older adult?*"), is answered from the moment that the whole platform was conceptualized and designed, using components derived from low-cost IoT solutions on the market, also integrated with software resources and services available for this purpose.
- The second question, Q_B ("*Through an interaction system, is it possible to trigger a triage system, with the older adult, to determine the need of intervention?*"), is answered by the triage mechanism and feedback request, where the user can answer by voice, simple questions, with a binary input of "Yes" or "No".
- The third question, Q_C ("*With this platform, is it possible to determine potential dangerous situations, reducing the time of perception and intervention?*"), is answered by the study and implementation of the core module ICAN(se)E, where it can determine in real-time abnormal situations, with data processing using machine learning models, which represent potential risk situations during the daily activity of the senior.

6.2.Limitations

The conceptualization of this platform aims to solve a complex problem effectively. Thus, this solution contemplates the integration, not only of a large number of components, but also the implementation of a set of distinct functionalities. Given the complexity and extensibility of the proposal, being this work limited in time, there are some limitations, which are intended to be overcome in the future.

Is evident that all the conceptualized components in the design of the platform have been developed, but they require a significant investment in their integration. Due to the importance of the triage mechanism, for validating her/his status with the older adult, it needs some improvement to allow a better interaction by voice, beyond the simple binary inputs, which would be beneficial bidirectionally.

Throughout this dissertation, significant work was done at the level of data analysis. Since it is in this computational work that the whole platform is based, a significant investment would be fundamental, to extract more knowledge from the data analysis, making the statistical analysis more complete, which would enable a more substantial number of illations, even by the caregiver. Adjacent to the machine learning process would also be the mechanism of voice interaction with the user, validating the analogies made by the platform, allowing the system to extend its knowledge in an autonomous way, such as in the classification of daily activities performed by the senior.

Overcoming these limitations would allow us to achieve a solid foundation with great potential for future growth.

6.3.Future Work

At this stage, there are the solid foundations of a platform that aims to meet the needs of the caregiver, in the task of remote monitoring and follow-up of a senior in her/his care, to act in useful time, whenever necessary, to ensure the well-being and safety of the senior. To the set of functionalities developed, this topic adds all the development considered necessary to complete the proposed platform. The conceptualization model proposed and the results obtained, from the implemented platform, allow idealizing the growth and scalability of it. For this, a set of functional areas was identified, where a significant improvement would be possible, either in terms of structure, execution and performance.

To make this platform a more complete solution, it would be necessary for the future to develop an administration module, which would provide the user with tools for managing the platform, not only in terms of the configuration of the devices that make it up but also in terms of parameterization and operation of the same. This tool would be fundamental for the use and joining of solutions and IoT devices already on the market, in a single platform to be integrated and used as a whole, as long as possible to communicate with the implemented platform, thus providing a wide range of data for analysis. This module, to be manageable, should contain a high technical abstraction and a *user-friendly* interface that allows the manager (which can even be a regular caregiver) to carry out this same platform management, without the need for extensive technological knowledge. Corresponding to these requirements, it would then be possible to dynamically install new sensors on the platform, make the system customized to the reality of each user and obtain a solution appropriate to individual needs.

Would also be positive to invest more in the triage module to improve its integration with the other components of the platform, thus making the interaction by voice more fluid and consequently more useful. At the level of information extraction, the data from it needs to be better analyzed, boosting the results. Thus, it would be beneficial to readjust the way they are presented to the user, making the information more dynamic using information visualization[40] technologies.

One of the obvious ways to evolve the conceptualized platform is to improve the processes of feature extraction and decision making, applied in the ICAN(se)E module, being a possibility to adapt other classification processes. Based on the principle of functioning of neurons in the brain, neuronal networks are complex algorithms that work in layers. These layers receive input from the previous layer and do the processing until a result is obtained. More layers increase the precision but make the algorithm slow. They work better than other algorithms, but due to their computationally heavy characteristics, they have not gained popularity in the past. Nowadays, due to the exponential improvement and computational gain of modern processors, they have become a major solution. They are often used for sales forecasting, financial forecasting, and anomaly detection in data processing and language. Following, it is considered the application of *deep learning* algorithms, which use neuronal networks and constantly evolve the model in which they work using new data. They learn and improve themselves, analogously to the behavior of a human being. Besides the techniques mentioned, it would be interesting to integrate unsupervised classification algorithms, to enhance the results from the extracted data. Periodically, the determination of heuristics for adjustment and recalculation of mean values used to determine the patterns known by the platform, could be a way to increase the accuracy of the obtained classifications. Thus, the attributes of the algorithms would be dynamically adjusted, based on the previous readings, allowing the platform to always act according to the current reality.

The integration of dedicated hardware would be a way not only to optimize the implementation of the platform but also its resource consumption and especially the decrease in the final price of the platform. Thus, the possibility of developing a *wearable* device, in this case, similar to an intelligent wristband, which would serve as a *gateway* between the sensors on-site and the platform, optimized for this purpose, both in terms of autonomy and performance, computationally capable of computing algorithms based on the sensors that compose it (such as detection of falls and cardiac anomalies), being easy to use in everyday life, without disturbing the normal activity of the user. With the help of a dedicated device, a set of functionalities to the platform such as alerts related to the exit of the older adult from their own home would be easily implemented in a modular way, which would enable the activation of location recognition abroad, especially useful in situations of evolution related to mental diseases. The modularity of the platform enables the integration of several low-cost IoT devices, from where those on the market can be found several home automation solutions that, by using shared

[40] Information Visualization (InfoViz): is the study of visual (interactive) representations of abstract data to reinforce human perception.

communication protocols with the platform, allow their easy integration and would significantly increase their functionalities in terms of task automation.

Another important principle is the integration of modules that allow the design of *gamification* activities to make seniors active while they are being monitored. Therefore, these activities for an active life should be used according to the senior's profile, functioning as challenges that can be collaborative or competitive. In this way, and with the use of modularity, it would be possible to accompany their natural aging process, adapting the platform to their specific needs, promoting the maintenance of their daily activity.

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A

Appendix

The following are some appendices, which not only complement the work carried out, but also substantiate some results obtained with it.

A. ICAN(b)E Platform Data Model

Relational model to support the data persistence of the ICAN(b)E platform and ICAN(se)E module.

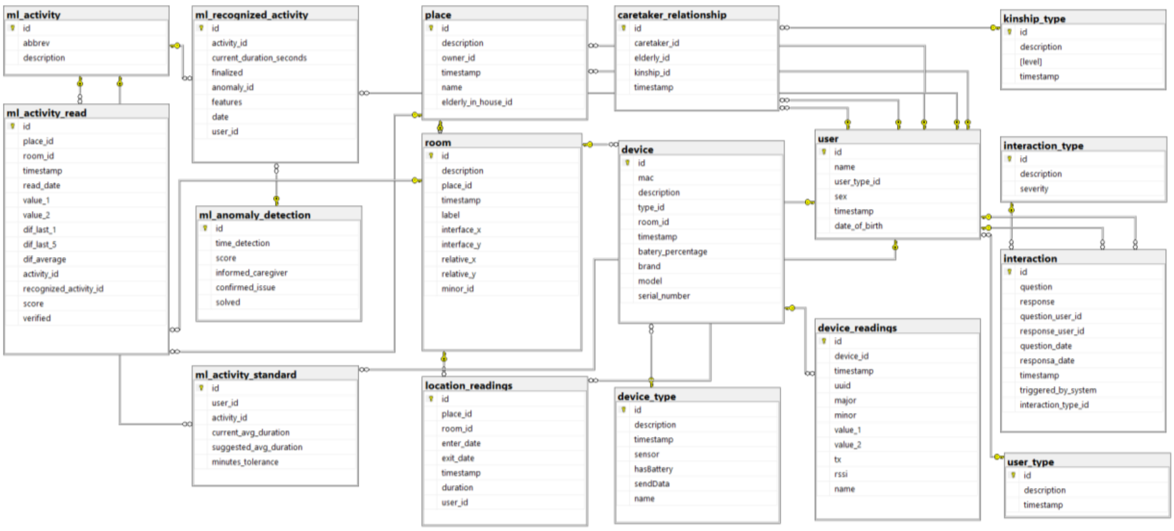


Figure 31 - Diagram of the relational model of the SQL persistence database

B. Anomaly detection model training

Results obtained from the training process of the machine learning model for detection of anomalies and time series, from a set of data consumed by the platform:

```
Detect temporary changes in pattern
======Displaying anomalies in the activity duration data==========
Date            Duration (s)    Alert   Score      P-Value
01/07/2020      360             0       -145,35    0,50
02/07/2020      420             0        -83,96    0,00
03/07/2020      360             0       -193,51    0,03
04/07/2020      480             0        -48,88    0,08
05/07/2020      300             0         49,62    0,01
06/07/2020      360             0         27,71    0,18
07/07/2020      480             0         28,03    0,24
08/07/2020      600             0        350,75    0,00
09/07/2020      420             0         -8,41    0,48
10/07/2020      300             0       -163,45    0,22
11/07/2020      660             0        268,83    0,09
12/07/2020      540             0         -7,73    0,50
13/07/2020      480             0        -31,90    0,46
14/07/2020      420             0       -142,65    0,25
15/07/2020      360             0       -162,47    0,24
16/07/2020      360             0        -32,06    0,49
17/07/2020      420             0        -41,50    0,49
18/07/2020      480             0        -22,51    0,47
19/07/2020      540             0        142,12    0,18
20/07/2020      540             0        232,84    0,11
21/07/2020      360             0       -105,04    0,32
22/07/2020      420             0       -164,28    0,22
23/07/2020      360             0       -164,42    0,23
24/07/2020      300             0       -166,79    0,24
25/07/2020      300             0       -198,67    0,20
26/07/2020      360             0       -262,70    0,12
27/07/2020      300             0       -254,94    0,15
28/07/2020      360             0        -29,56    0,44
29/07/2020      540             0        139,93    0,18
30/07/2020      360             0       -102,87    0,41
31/07/2020      480             0         -3,14    0,40
01/08/2020      390             0         -2,60    0,41
02/08/2020      300             0        -85,71    0,42
03/08/2020      1260            1        723,98    0,00 <-- Spike detected
04/08/2020      480             0        -45,56    0,47
05/08/2020      447             0        -37,15    0,49
06/08/2020      540             0        -27,80    0,49
07/08/2020      570             0         53,81    0,36
08/08/2020      510             0        -11,96    0,44
09/08/2020      360             0        -72,26    0,45
10/08/2020      432             0         72,92    0,31
```

The model was able to correctly and with maximum certainty assess the anomalous value detected on August 3, 2020, considering the known average duration values for the same activity.

C. Interfaces and scenarios of use

This section presents some of the user interfaces of the ICAN(b)E platform applications, which are used by the caregiver, who has access to manage her/his own account and its components.

Mobile Application - Notifier System

The notifier system consists of an Android application, which provides the caregiver in real time with a tool capable of keeping him/her informed about the state of the older adult in her/his care. This application is installed on a smartphone that requires the use of mobile data in order to obtain information from the central server of the platform.

Authentication and Registration

The following are the authentication or user registration interfaces. Authentication is shared with the whole ecosystem of the ICAN(b)E platform, so the authentication credentials will be the same as for accessing the web application. In case the user does not have an account created yet, s/he can do it directly in the mobile application, being automatically created for use throughout the system.

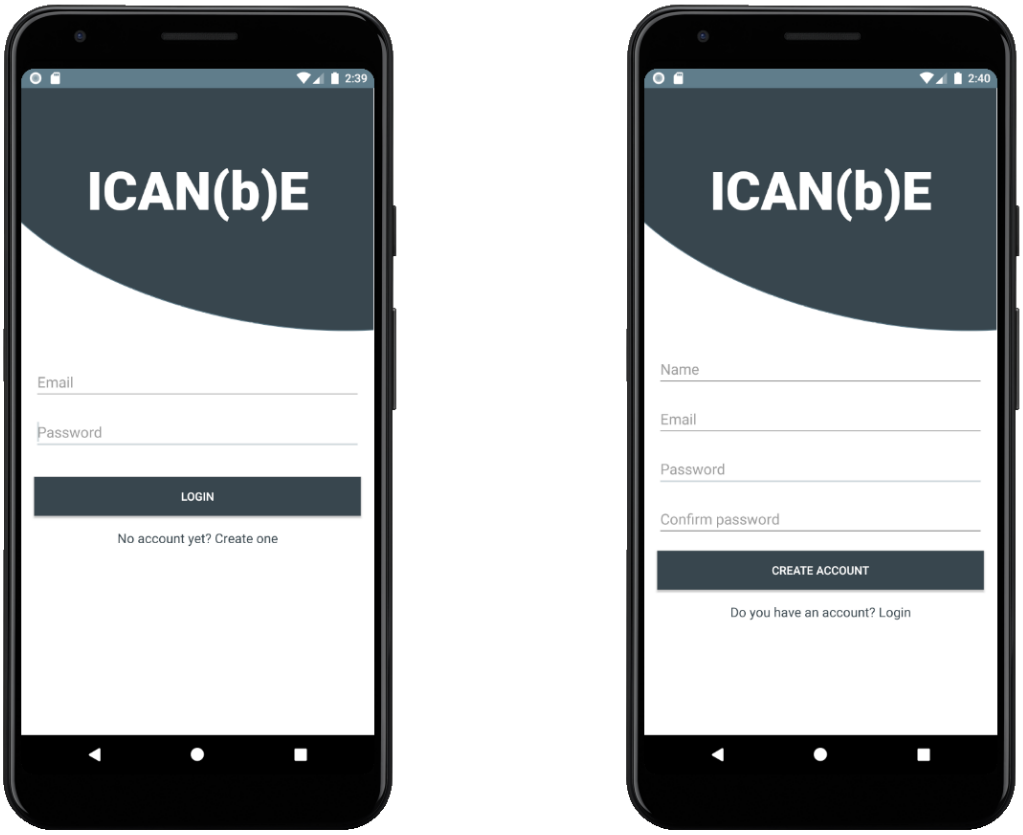


Figure 32 - Notifier System - Authentication and registration interface

Main Menu

Main menu, sharing a design across the entire platform, with a neutral color scheme, implementing the Material Design libraries, with a validated usability. The visual identification of the elements is simple, and easily identified by the user, as is the case of the rim surrounding the avatar or photo of the older adult, which can range from a neutral tone (grey), green (when in a validated state), yellow (when in a situation of potential risk) and red (when detected some anomaly, which requires intervention).

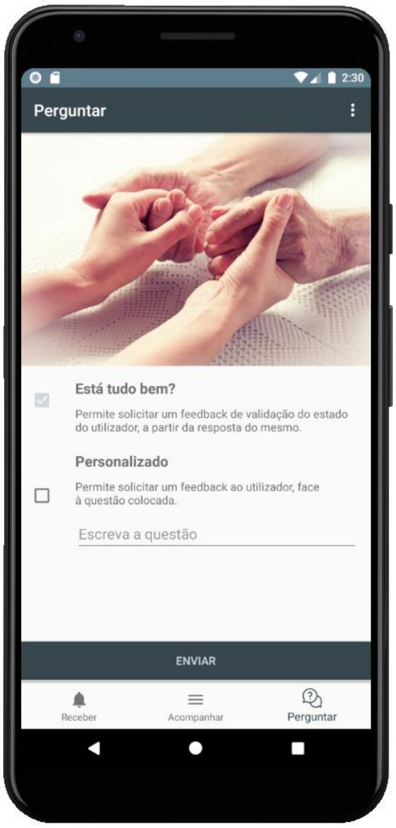
Also presents information regarding the daily routine, last recognized activity, activity time statistics, among others, according to the caregiver's configuration.

Figure 33 - Notifier System - Main Menu

Feedback Request

This interface allows the caregiver to send a feedback request, which will trigger, in the older adult's own home, using a smart column, a question by voice, in order to establish by this way a communication with the older adult. To this request, the older adult can respond using this interface by voice, with a simple answer (binary) of "yes" or "no". In addition to pre-established questions regarding the older adult's condition, personalized requests can also be created, with questions introduced at the time of sending. Questions by *default* can be added in order to be used in future situations. The answers obtained from the requests placed, or even the lack of answers, will be found in the "receive" menu.

Figure 34 - Notifier System - Feedback request menu



List of received notifications

The notifications are divided into two distinct groups, given the way they are created. One is a notification regarding requests for feedbacks from the caregiver, where the question and the respective answer are included. The remaining notifications refer to events triggered by the platform in an automatic way, either when the detection of a potentially critical activity or anomaly detection at a certain point of the daily routine, or statistical information regarding the older adult monitoring. The user can also manage the notifications received, as well as delete the desired set of notifications. All the notifications presented in this list are presented using *push notification*, promptly, when triggered.

Figure 35 - Notifier System - Notification Reception Menu

Notification

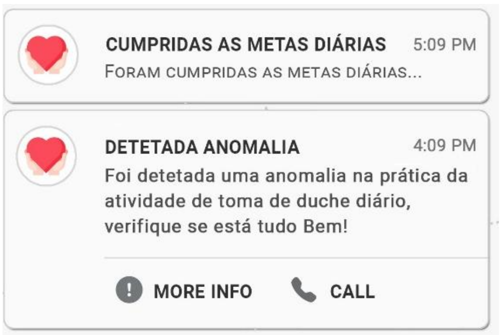


Figure 36 - Notifier System - Example of personalized notifications

The notifications are automatically presented on the caregiver's mobile device when triggered by the platform. Can be informative only or require some kind of action. When some type of action is required, the periodicity of the alert is more accentuated.

ICAN(b)E – Web Application

The web application allows the user to have access to all the information coming from the ICAN(b)E application, as well as to manage the whole system and its components. Below are some of the *layouts* to which the user has access.

When a user accesses the platform, the main page is displayed. In case s/he or she is logged in, s/he or she is automatically redirected to the administration page. Otherwise, s/he can perform the authentication or account registration..

Figure 37 - ICAN(b)E - Main Page

The authentication module allows you to login or register an account. The credentials will be shared between all the components of the platform, including with the notification system (mobile application).

Figure 38 - ICAN(b)E - Authentication Module

In the main menu, the caregiver can access a set of system features. Among them, the modules:

- Accompaniment - module of accompaniment, which allows the caregiver, in real time, to accompany not only the activity routine of the older adult in her/his care, but also their location in the home;

- Visualization - visualization module that allows access to the set of records of the routine and daily activity of the older adult;
- Receive - module that allows the reception and recording of all responses to the feedback requested, as well as the notifications triggered by the system itself;
- Ask - module that allows you to make a feedback request to the older adult, regarding their state or simple questions that need binary answers (positive or negative);
- Analyze - statistical module that allows the caregiver access to complete statistical reports, from the analysis of the data extracted from the platform components.

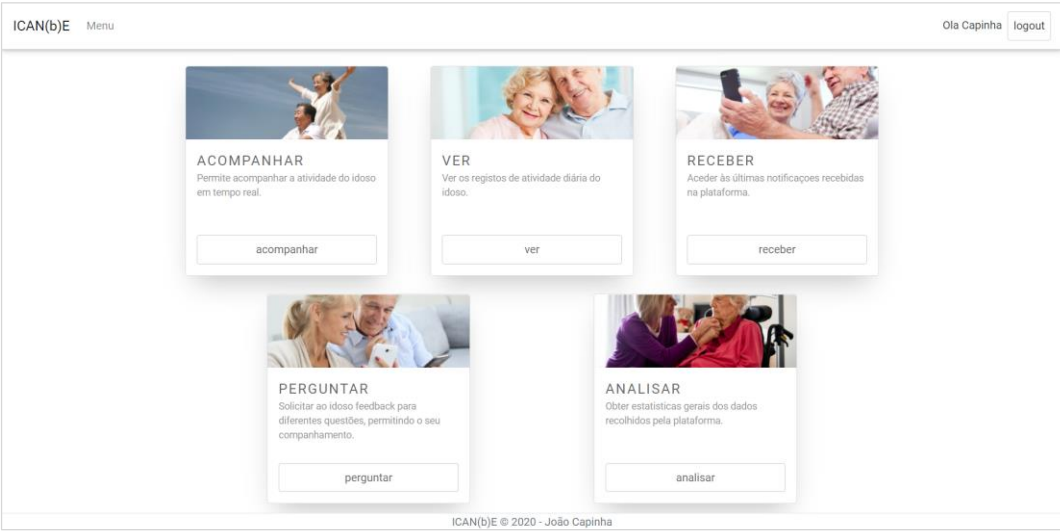


Figure 39 - ICAN(b)E - Main Menu

The indoor location module allows the identification, with maximum precision and in real time, of the location of the older adult in her/his home, as well as the result of the classification of the activity practiced at the moment.

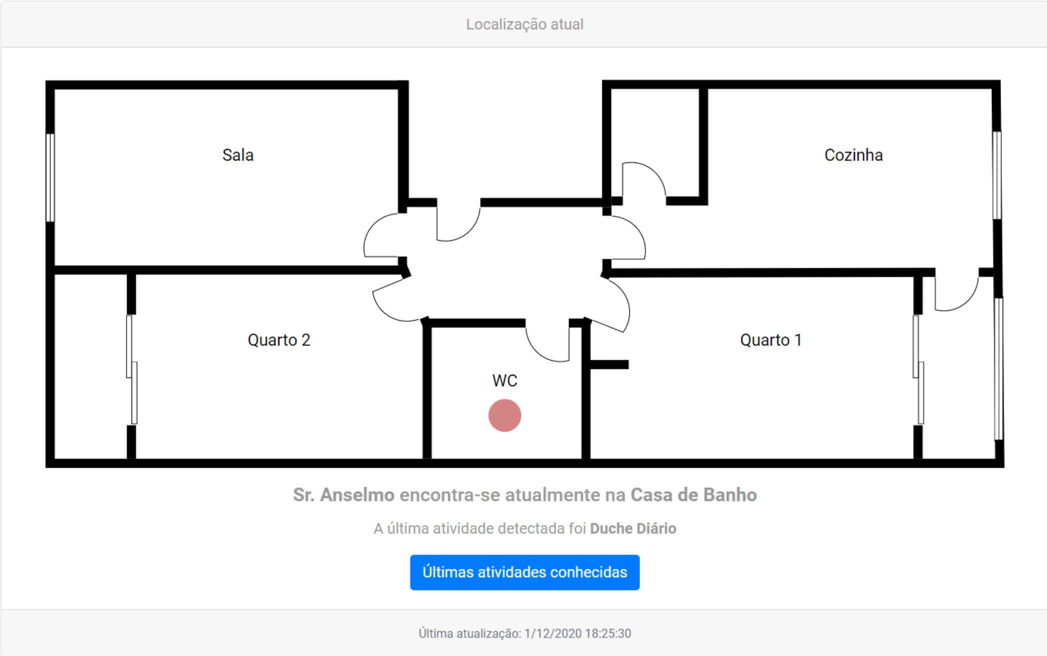


Figure 40 - Figure 5 - ICAN(b)E - Indoor Localization Module-

When an activity is detected, through data collected from environmental sensors in the room where the older adult is, the caregiver can access the referred data, oscelations and graphs that indicate, in a time series, the period in which the activity was practiced.

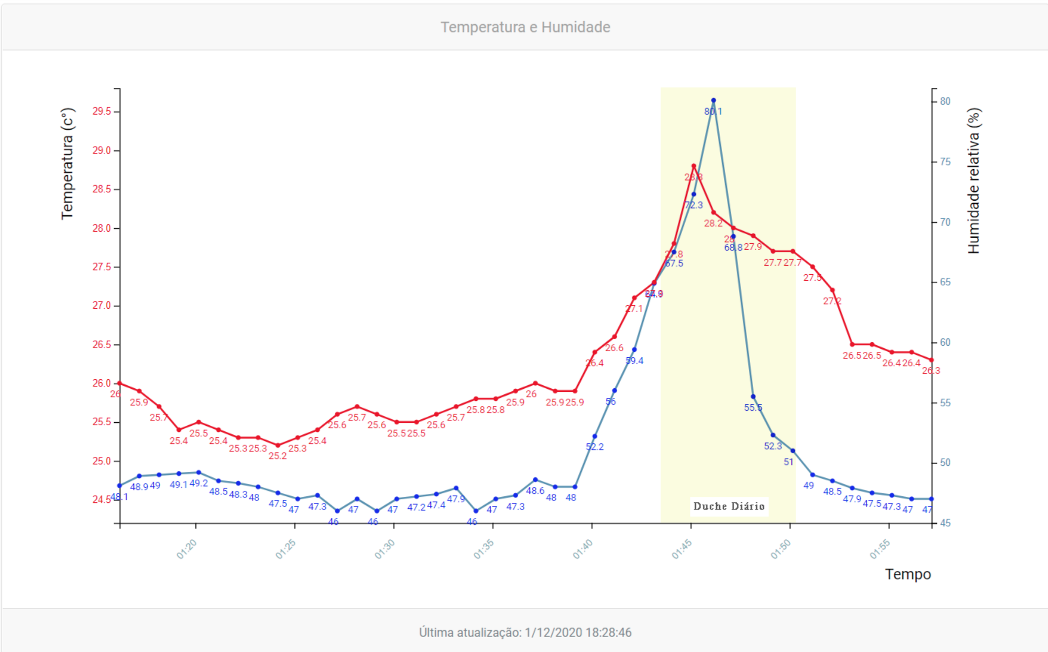


Figure 41 - ICAN(b)E - Data from environmental sensors

The statistics module aggregates a set of information regarding the daily routine of the older adult, which is presented to the caregiver in a dynamic way, allowing a filtering of the data to facilitate their analysis and generation of *reports*.

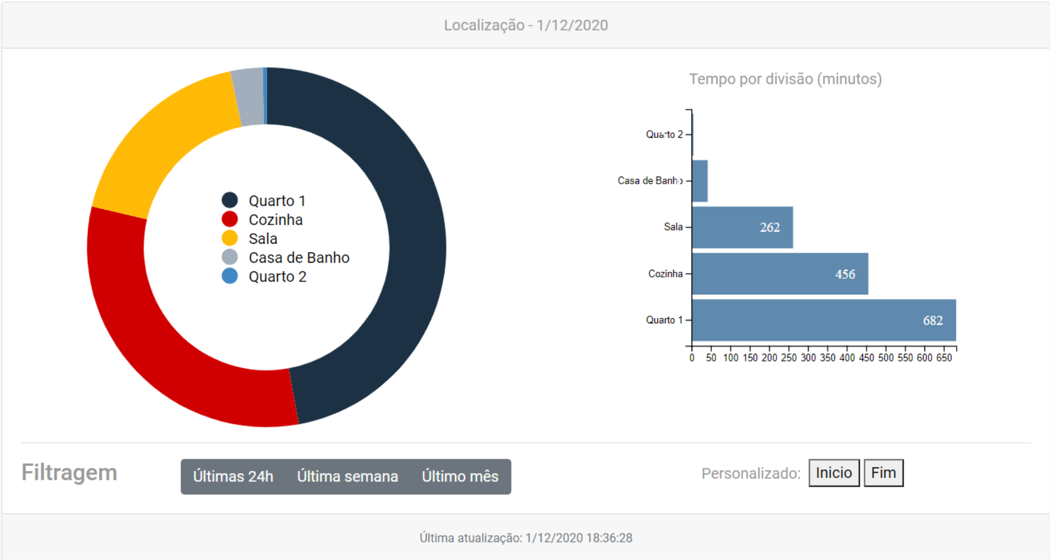


Figure 42 - ICAN(b)E - Statistics Module, time per room