INTRODUCTION

The Internet of Things (IoT) it's a collection of Things (sensors, cellphones, GPS locators, RFID systems or other smart objects) that are identifiable, trackable, and connected to the internet, providing a large scale of information access.

Different protocol stacks and ecosystems were developed for IoT, resulting in a communication incompatibility, contributing for a fragmented scenario without middleware gateways. Web-of-Things emerged from this scenario to provide connection between Things using web technologies, enabling their access, discovery and management (Fortino et al 2017; Guinard et al 2016).

Due to the huge amount of data generated from all constraint devices (Things) connected that can be accessed and managed from the internet, new challenges occur in storage and processing all data. Cloud computing, which is a set of architectures and models that concentrate software and hardware resources, offering them as-a-Service to users, such as Platform as-a-Service (PaaS) which provides computer platforms that can include operating system, programming languages, databases, web servers, and other environments, Software as-a-Service (SaaS) where the cloud manages the infrastructure and a software may be deployed for client usage or Infrastructure as-a-Service (IaaS) that aims to provide virtual machines, servers, storage, load balancers scalable and redundant depending on users requests, could be the answer to these questions. (Guerreiro J. et al)

Sensing as-a-Service (Se-aaS) surfaced from this scenario to respond to these challenges as a business model, allowing sensor owners to share data into a cloud of sensor Things to be collected by data consumers, paying it as-a-service. The authors Distefano et al (2012), presented a step towards to a creation of a Cloud of sensors and actuators (devices and/or cloud can perform actions), by introducing an architectural scheme that responded to the challenges using smart devices, Sensing and Actuation as-a-Service (SAaaS).

The Portuguese Health Ministry created a Health Portal on which all public medical and health technical staff can access patient's data, exams, reports, and analysis performed inside the Nacional Health System (NHS) Institutions, so that when someone is attended anywhere in the country, all health professionals can access the data registered, diminishing costs, being more effective and productive. This platform is essential for patients and medical staff to visualize patient's medical data, but only the ones registered on public NHS Institutions, there is no connection to private health institutions.

Nowadays, the aging of population and growing life expectation is a serious concern to all national health systems, not only to create health conditions in the health system but to provide care to elder people. In Portugal, the aging index grow from 27.5% in 1961 to 182.7% in 2021 (Pordata 2022), being essential to create conditions to promote health and wellbeing, increasing functional capacity, autonomy, and life quality to people while they are aging.

Many studies have been addressing the connection of sensors and technology to the aging, such as remote health monitoring, fall detection and elder surveillance.

This study intends to propose the design of a preliminary framework model which allows the connection between all Things that can remote monitor, detect and actuate in elder's health, retrieving and integrating data into the Health Portal System to be available to all medical and technical staff anywhere in Portugal.

The proposed framework model is suitable for IoT SAaaS business models, supporting multi-sensing client applications and multi-sensor supplier's deployment, Thing's mashups, and multiple domains integration.

The remainder of this article is organized as follows. In section Cloud-Based Sensing and Actuation as-a-Service the main system architectures and functionalities are discussed. Section Related Work discusses the work done on the connection between sensor systems and elders health. Section Framework Model presents the design of the framework model proposed to interconnect all Things into the Portuguese Health Portal and section Conclusion, concludes the article.

CLOUD-BASED SENSING AND ACTUATION AS-A-SERVICE

Cloud computing objectives is to provide on-demand computing and storage resources to users, using virtualization techniques and proving an as-a-Service business model.

Se-aaS was introduced by Sheng X. et al (2013) and aimed to provide sensing services on cloud environment, using mobile phones, describing system functionalities and tasks to implement the system. The functionalities described by the authors for a Se-aaS sensor cloud were:

- **Web interface**: it should have a web interface to collect requests from users.
- **Generating sensing Tasks**: the cloud should perform generic sensing tasks containing the request information in a standard format.
- **Tracking mobile phones**: the data should be shared to all smart phones, so the sensor location and energy status should be available and have a way to push the tasks into the mobile phones for data collection.
- **Recruiting Mobile Phones**: Sharing the mobile sensors of the smart phone was the main idea, therefore a way or mechanism to recruit and incentive mobile phone users to share their sensors must be implemented.
- **Scheduling of Sensing Activities**: There must exist an algorithm or policy to schedule sensing activities on the recruited mobile phones, for data to be collected.
- **Managing Sensors**: The sensors on the mobile phone must be managed to collect and store data into the cloud.
- **Processing and Storing Data**: A database is required to store the collected data from the mobile phones sensors and to be able to deliver reports to the users.

The authors, Sheng X. et al (2013) also introduced scheduling algorithms to address sensor energy issues to load sensor data into the smartphone platforms and an incentive system to attract users in participating in the project, being therefore, the first approach to Se-aaS business model.

Figure 1: Se-aaS generic environment

The Se-aaS model emerged from the processing and storage needs and has three main actors (Distefano et al 2012), Sensor Providers or Node Owners, Cloud of Things or Sensing Cloud and Data Consumers or Software Application. Figure 1.

Those three main actors are also the three architectural infrastructural layers (Perera et al 2014) of the Se-aaS model:

- **Sensor Providers and Physical Sensors or Things:** This layer consists in sensors or actuated sensors owned by sensor providers that may register those devices in the Se-aaS cloud infrastructure to share sensor data. The providers must maintain, manage and control the Things to be always available and being able to share the data they gather (Kim et al 2016).
- **Cloud Infrastructure or Cloud of Things:** There are several types or servers on a cloud infrastructure to process, store and provide the services (Figure 2):
    - **Portal Server:** This server objective is to have a web interface that responds to user's logins, sensor owners and data consumers. Sensor owners can register or deregister their Things and view the usage of their devices obtaining detailed reports. Data consumers can subscribe sensor or sensor groups and access their data, controlling how many times data must be retrieved, check sensor or sensor groups status and the unsubscribed whenever the consumer desires. The server also forwards the consumers sensor subscriptions to the Provisioning Server for virtual machines creation, modification or removal, depending on the action (Kim et al 2016).
    - **Data Storage Server:** This server main goal is to ensure data storage in the databases of the user's information, the sensors or group of sensors or the gathered sensor data (Kim et al 2016).
    - **Monitoring and Management Server:** is responsible for providing a solution that responds to multiple consumers (multi-tenant solution) on the cloud, be able to perform scaling and load-balancing between the created virtual machines to respond to consumers requests and available sensors or group of sensors. This server is also responsible for retrieving sensor's data and check sensor's health status, send the data to the Data Storage Server to be stored and available for consumer usage. The monitoring and management server is the most important in the infrastructure since the provisioning is dynamic and based on live physical sensors, so it must have a location and status aware knowledge base for the Provisioning Server not to use the offline sensors while provisioning them to the consumer (Kim et al 2016).
    - **Provisioning Server:** This server is responsible for the creation of virtual sensor groups (groups of sensors with the same functionality and similar properties) on-demand, depending on consumers requests registered on the Portal Server. The Provisioning

Server will create and reserve virtual machines when receiving the request from the Portal Server. When the virtual machine is ready, the virtual sensor group is provisioned and stored on the Data Storage Server, for the Portal Server be show the data retrieved to the consumer (Kim et al 2016).

- **Consumers:** The consumers through the web page available by the Portal Server will place their requests and start receiving real-time analytics from the sensor or virtual sensor groups. Consumers can download the data or integrate through Application Programming Interfaces (APIs) to connect to their own applications (Kim et al 2016).

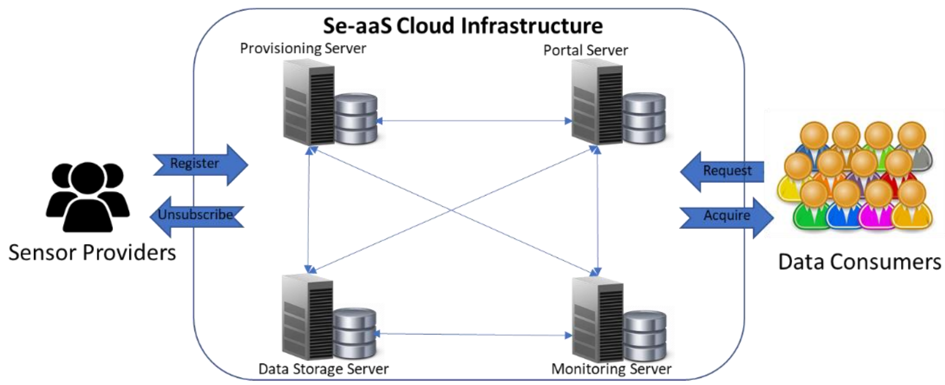

Figure 2: Se-aaS architecture

The workflow within this model starts with the register of Things by the sensor owners using the Portal Server as the interface. Those Things are stored by the Data Storage Server on the databases after a location and status check performed by the Monitoring and Management Server.

On the other side, the clients register themselves on the Portal Server and place their sensor data requests and the Provisioning Server will create the virtual sensor groups that better can respond to the consumers request, using the information registered on the Data Storage Server where all sensors are stored on the databases. The Monitoring and Management Server starts the data retrieval in real-time and stores the data on the Data Storage Server databases. The results will be visualized by the consumers using the Portal server.

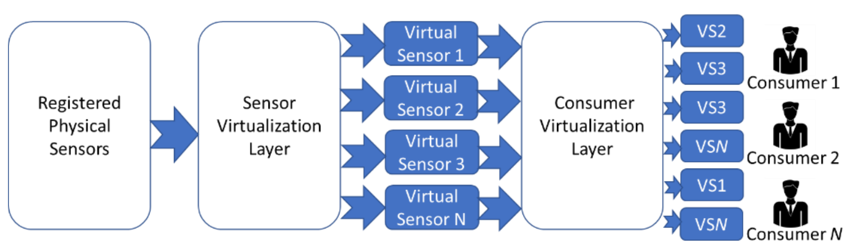

Figure 3: Virtualization Layers in Se-aaS

Kim M. et al (2016) describe the Se-aaS infrastructure functionalities, adapted from Sheng, X., Jian Tang and Xue, G. (2013):

- **Virtualization:** Virtualization of sensors is used in the dynamic provisioning enabling device management and customization by consumers requests, where a single Thing can be linked to one or to multiple consumers. Virtual sensor groups can be created and provided for specific usage. (Figure 3).

- **Dynamic Provisioning:** Consumers can request a large set of devices on each request, due to the dynamic on-demand creation on provisioning of virtual sensors that respond to one or more requests and one or more consumers. The provisioned virtual sensors properties must be as close as possible to the consumers requests.
- **Multi-Tenancy:** Multi-tenant architectures respond to a set of consumers and permits the sharing of sensors or Things and the retrieved data for consumers usage, providing dedicated instances for each sensor provider.

Se-aaS in smart cities context is discussed by Perera et al (2014), addressing technological, economic and social perspectives. Petrolo et al (2017), propose also, in smart cities context, a global approach for sensor semantic annotation at the cloud for sensor aggregation and create a technological agnostic architecture to integrate and deploy Things, ignoring their physical and logical architecture. Their approach foresees the convergence of IoT platforms and ecosystems needed for smart cities.

Hsu et al (2014) and Misra et al (2014) address semantic selection. The first proposes a context-aware sensing service architecture applying selection and search options for user preferences, accuracy, energy consumption, sensing range, etc. The author proved that by the selection of requirements and parameters using semantics, decrease power consumptions in comparison with traditional search schemes. Misra et al (2014), designed a framework for selection of the optimal gateway in a sensor cloud using semantics applied on remote health monitoring distributed on different geographic locations.

Multimedia Se-aaS was discussed by Lai C.F., Chao H.C. et al (2013), Lai C.F., Wang H. et al (2013), Wang H. et al (2017) and Xu Y. and Mao S. (2013). The first work developed a real-time transcoding mechanism for HTTP live streaming using cloud as basis and hand-held devices like mobile phones or tablets. Xu Y. and Mao S. (2013) discuss the energy consumption, offload computing tasks, limited bandwidth, Quality of Experience, privacy and security technical challenges and how to minimize costs using rich media applications on mobile devices in a cloud computing environment.

Lai C.F., Wang H. et al (2013), discuss an approach on network and device Quality of Service using cloud based mobile streaming. The main goal was to provide multimedia data using interactive mobile streaming services adjusting the transmission frequency interactively and multimedia transcoding dynamically to avoid power waste and low bandwidth issues.

Wang H. et al (2017), presented a resource saving cloud-edge IoT and fogs Multimedia Sensing as a Service (MSaaS). The authors developed a framework for cloud edges and fogs that analyses frequency, data dependencies, temporal domains, and interaction in order to optimize resource allocation at the cloud-edge IoT and fogs.

Se-aaS model works on cloud for sensors data to be available for cloud client's accesses, similarly to other aaS models. Resources must be registered by sensor owners and dynamically provisioned on client or data consumers demand, being as flexible and fast as possible to be afterwards available for other requests. The data consumers or cloud clients must register themselves through a subscription and the costs they have are directly indexed on the Things and data they access and collect. The sensor owners must be incentivized to register their Things and they will collect their return (amount of money) also indexed to the accessed done on their sensors. This is the business model. Challenges to design and plan such a system are:

- The complexity of the system should be hidden, and services or applications must work without much overhead.
- The data collection must be on a low cost-of-service per consumer and prepared to be scalable.
- Dynamic resource provisioning to client requests must be efficient.

Several models were developed to optimize resource allocation in Se-aaS, Guerreiro et al (2019), developed a model where embedded mashups (workflow wiring together a set of Things) into the cloud to diminish delays of multiple travelling sessions between cloud and consumer and created a resource allocation heuristic with three different strategies to compare which one would outperform each other.

The same authors (Guerreiro et al 2020), in another article, developed an adequate mathematical optimization model for resource allocation and a heuristic that outperformed the state-of-the-art method, being very close to the mathematical optimization model, fulfilling more consumer requests, using less devices with lower materialization costs, meaning that the allocated Things are very near to the properties requested by the consumers.

Sensing and Actuation as-a-Service is a cloud computing business model, where sensor providers register their smart Things to provide real-time data to consumers with scalability, security and redundancy, assuring multi-suppliers sensor providers and multi-consumers data retrieval, while the cloud infrastructure assures storage, processing, virtualization and security.

RELATED WORK

Many studies have been discussed throughout the years that support the interaction between sensor systems and elderly care.

Using time series clustering to detect elder daily routines, an algorithm to identify day-to-day activities deviations in patterns and generate alerts to healthcare providers was developed by Hajihashemi et al (2014). Using time series sensors with a hierarchical cluster approach to extract periodic patterns in a retirement community in Columbia MO, having a motion pressure and depth sensors network, the study aimed to quantify bathroom visits and verify the duration, the number of visits and the average time between visits. The computational algorithm developed by the authors successfully extracted routine bathroom visits of the elderly residents. Using the hierarchical clustering approach, they detect the frequent sensor sequences with a high-rate average of 0.84, therefore supporting the robustness of the used method.

An approach on surveillance with noncontact sensors framework was presented by Wang Y. (2017) to provide a temporal and spatial context on elder's daily routines using passive infrared (PIR) sensors. The conclusion of the authors study is that their system shows that using a single type of ambient sensors it is possible to detect and monitor the elder's daily routines and routine changes. The proposed method is accepted by older people since it's less intrusive due to the noncontact sensor's usage.

A hybrid fusion-based data sensor system to determining elder's daily activity and routines is proposed by the same authors, Wang Y. et al (2018). In this case, the authors propose a hybrid sensor-based human activity recognition (HAR) using a unique data fusion method combining wearable sensors, to identify specific daily routines and ambient sensors for surveillance. The room-level location information is used in the data fusion to trigger the classification models trained by the wearable data. The development of a classification algorithm using vector machines allows the goal to explore and improve recognition accuracy. Results demonstrate that the data fusion between the wearable and ambient sensors resulted in a improved accuracy compared with the scenario of recognizing all the activities only with wearable sensors.

A preliminary study for remote healthcare system with activity classification for elder people using body sensors was presented by Koçak et al (2018) using radial basis function networks, k-nearest neighbor, and vector machines as the support basis of the study. The results showed that the best classification performance was 99.8%, but with the application of the feature selection, the performance decreased to 99.4%, nevertheless, with this study, it was possible to create a remote-controlled care system that reports elder people information to family or care takers when hazardous situations occur, such as falling or fainting and directly assigns a medical emergency unit to the corresponding address in such cases.

Casagrande et al (2018) introduced a preliminary sensor event prediction system using recurrent neural networks with a Long Short-Term Memory in smart homes for elder people using binary sensors to predict the event in a sequence. The authors used in an apartment fifteen sensors, seven motion sensors in each area of the house and on the bed to determine if the elder is in the bed, four magnetic sensors on the doors and cutlery drawer and four power sensors on appliances, nightstand lam, coffee machine, TV and living room reading lamp. The sensors were connected using a wireless network into a Raspberry Pi 3 that receives the data and transfers it onto a secure server storage. A comparison was done with the results of the implemented system with the Long Short-Term Memory network to the baseline method from similar work previously done. The implemented system obtained a peak prediction accuracy of 69% and 75% for 13 and 5 sets of sensors, while the accuracy of the baseline was 58%. The results show that a much higher prediction accuracy is required before such algorithms are applicable.

Xu G. et al (2013) discussed another important elderly issue, which is the elder falls. The authors proposed a body sensor network communication system with an acceleration sensor node placed on the elder’s head, a pulse sensor on the wrist, two plantar pressure sensors on the ankle and a sink node on the waist to collect real-time information and communicate with a remote computer through a Bluetooth module. The system detected correctly if a fall event occurred, or a pulse change and the hardware implemented provided a good platform for the elder fall algorithm research.

A fall characteristic monitoring system based on machine learning was proposed by Hsieh C. et al (2018), to support clinical professionals to assess fall events causes and create prevention strategies, consisting in a high accuracy fall event detection and fall direction identification algorithm. The authors used a tri-axial accelerometer to measure motion acceleration and a fall event detection algorithm that detected seven types of falls and six types of Daily Living Activities (DLA). The authors were able to predict falls with a precision of 98.67% and 97.57% for fall direction identification accuracy.

A deep-learning based near-fall detection algorithm for fall risk monitoring classification system using a single inertial measurement unit was presented by Choi A. et al (2017) et al to categorize three classes, falls, near-falls and DLA using accelerometers and gyroscope sensors to acquire acceleration and angular velocity signals. The neural network architecture proposed with a modified directed acyclic graph convolutional neural network which captured sensor’s data, was able to predict fall, near-fall and DLA with 7% more accuracy than the traditional neural networks systems. In near-falls case, the results reached a total of 98% accuracy. The authors conclude their study adding that the deep-learning algorithm developed, trained by combining acceleration and angular velocity, showed better performance then other algorithms in pre-impact fall detection.

Jiang Y. (2022) addressed the construction of an intelligent system for elderly’s health and care in a physical medicine and smart sensors integration perspective in China urban communities. Jiang Y. (2022) proposed a combination of medical resources and elderly care resources, rehabilitation and social resources model integrating smart health and elderly care smart devices into a service platform software able to realize health management services, elderly care services and telemedicine services based on IoT, to provide information support for China Government to build a complete health services and guarantee elder’s health services and daily life remote monitoring.

Hong Y-J. et al (2008) presented a novel method to recognize elder’s activities of daily living with accelerometers and RFID sensor. The objective was the classification of five body states with a decision tree and the detection of RFID tagged objects hand motion information with a Bluetooth based wireless triaxial accelerometers and iGrabber RFID reader. Their results show that the system can determine whether the elder can live normally or not with the reports being sent to the remote family.

The development of cognitive sensors was addressed by Gaddam A. et al (2010) based on an intelligent wireless sensor network to monitor the living environment of the elderly people when living alone to provide a safe, sound and secure ecosystem at home. The objective was to deploy inexpensive smart and cognitive sensors for monitoring the activities of the appliances with features to include the coverage, small obstructiveness’s, that would be easy to deploy, uses reduced energy consumption, low on maintenance and more acceptable by the elderly community. The system used radio frequency with a controller and an interface control software that recognized the activities of daily living and lifestyle of the elders to capture abnormal behaviors.

Another approach on elder care was also presented by Gaddam A. et al (2011), with a home monitoring system based on a cognitive sensor network to detect electronic device usage, bed usage patterns, water flow and others, including a panic button. The main goal was to detect any abnormal pattern in elder daily activities around their houses. The system generated warning messages to the care giver whenever any abnormal behavior was detected.

A fall prevention system was developed by Sumi L. et al (2019), introducing an accelerometer algorithm, Bluetooth Low Energy (BLE) modules in strategic locations and an alarm system to notify caretakers. The BLE sensors detected and send warning to the server which triggered the alarm system, preventing the elderly fall.

Another approach on fall detection during the usage of a walking assistant robot was studied by Wang S. and Zhang X. (2015) on where the authors proposed a multi-sensor data fusion based on a neural network, making full use of tactile-slip sensor, acceleration sensor and gyroscope to acquire the needed data and falling risk. The multi-sensor data fusion system structure basic principle was using multi-sensor data complement, process information in time and space to achieve interpretation consistency of the observed environment. The fusion center based on neural network was designed to use the different motion sensors characteristics and measurements to realize data fusion. Results show that the algorithm developed by the authors was better than using a single sensor for fall prediction and the system can recognize the fall tendency of the elders.

An investigation on the performance of a wearable distributed deflection sensor in arterial pulse waveform measurement was presented by Wang D. et al (2017). The sensor was built on a flexible material with a polymer microstructure and an electrolyte-enabled resistive transducer array, that enabled the pressurization of the sensor by two fingers on the artery to register the radial and carotid pulse signals. Signal processing algorithms were developed to extract the key tonometry parameters and calculate the pulse wave velocity and radial and carotid augmentation index. The results show variations of gender, hypertension and the calculated radial and carotid pulse wave velocity has a positive correlation with age, gender and hypertension, making this sensor a potential and unexpensive point-of-care for untrained individuals to keep track of their cardiovascular condition.

Daher M. et al (2017) proposed an elder tracking and fall detection system using smart tiles. The usage of force sensors and three-axis accelerometers concealed under intelligent tiles was the authors strategy to detect and recognize human activities such as walking, standing, sitting, lying, down, falling and the transitions between those activities. The proposal was a fusion between the measurements acquired by the force sensors and the decisions done by the accelerometer, providing accuracy, precision and efficiency. The pressure sensors (load cells) measure the load forces exerted on the floor implemented under the tiles allow to determine the posture of the monitored elder, standing, walking, sitting, falling, etc. and the developed algorithm aligned with the accelerometer signals determines if the elder has fallen and may trigger a quick assistance. The results presented showed the flowchart of the fusion between accelerometers and force sensors to be able to locate and track the elders, recognize their activities and detect fall cases.

Another approach, on older people remote health monitoring, was presented by Li H. et al (2018) with the objective to study assisted living on two types of sensing technologies: wearable (accelerometers, gyroscope, and magnetometer) and radar sensors, using information fusion to enhance activity classification accuracy, vector machines and nearest neighbor support, to automatically monitor the elderly activity and fall detection. The feature fusion level implementation is described with the concatenated data extraction from the sensors before introducing it into the classifiers, improving, therefore, substantially the accuracy. The conclusions indicated that the classification performance was improved from 78-85% with individual sensors to 98% using multi-sensory approach and the proposed classification fusion method.

Inertial sensors to detect fall risk were used for the assessment and prediction in older adults in a study performed by Montesinos L. et al (2018). The goal was to present a systematic review and meta-analysis in the sensor location relevance, the sensor task and their features, applying a statistical approach to identify their optimal combinations. Results show a high and significant interaction between sensor’s placement, task and feature categories to access the risk of falling. The framework developed for future study, highlights dependences among those factors and the review demonstrated the optimal features from inertial sensors for fall risk assessment in older adults.

Singh A. et al (2020) presented a review on sensor technologies for fall detection systems that aimed to provide a comprehensive technical insight in the previously done fall detection systems works, classifying the distinct approaches and the challenges encountered. The authors also had the goal to extend their study to provide an overview of each sensor technology such as accelerators, pressure sensors and radar camera-based and their fusion in a complete fall detection system, showing their strengths and limitations in terms of feature extraction, classification, performance and experimental datasets. The conclusions presented by the authors were the characterization of sensor technologies into acoustic, floor pressure, image, PIR, near field imaging, radar, ultrasonic, smartphone-based and wearable sensors-based systems and summarized the strengths and weaknesses of each technology to help researchers in the selection of the sensor technology for distinct applications.

McManus K. et al (2022) developed a data-driven metrics for balance impairment and fall risk assessment in older adult’s study using inertial sensors technology. Two studies were carried out by the authors, one with an inertial-based balance sensor assessment and the other to report a reliability analysis of inertial sensor postural stability measures and validation, comparing them with clinical scales. The authors also elaborated a fall estimation algorithm based on inertial sensors captured data and a method to improve the fall risk estimate, incorporating standard clinical fall risk data. The authors conclude that their study demonstrates the reliability of the balance and fall risk measures acquired and their validation in a large older adult group compared with the clinical scales. The results show from the fall risk classifier models suggest they are more accurate at estimating fall risk status then a model based on Berg Balance Scale or Time Up and Go test model, concluding that the algorithms used in the authors study are potentially useful screening tools for balance impairments and falls risk.

FRAMEWORK MODEL

As presented on the related work, many are the advances done using sensors and elderly health care, specially on fall detection, targeting physical medical parameters, triggering alert systems to care takers or family. Jiang Y. (2022) addressed the connection between smart sensors and the China Government health management services to provide information and improve health care and better daily life to older people.

This preliminary study intends to go further than that, integrating directly into the patients record the data retrieved from the sensors whatever they are, so the system must be agnostic to what features, characteristics or data sensors acquire. The objective is to integrate on a SAaaS cloud environment any type of sensors (Things) and deploy the data directly to the Portuguese National Health System to be, in a short period of time, available for medical analysis or intervention.

In Portugal all Portuguese people have a unique health process number, the Personal Patient Data Register, (PPDR) and a family process (FP) in each Health Center the family belongs to, so these two registers may be used to integrate the information gathered from sensors throughout the SAaaS cloud system into the Portuguese National Health System (PNHS) patient records.

As mentioned before the Se-aaS or SAaaS model, sensor providers register their Things into the cloud for consumers to be able to retrieve data from those sensors, after the cloud infrastructure dynamically provide virtual sensors corresponding as near as possible to what was requested.

In this study the usage of the SAaaS framework must be altered for the system to provide dynamically the sensors, and attach the data retrieved from the sensors attributed to a specific elder, integrate into his specific health care registration process, changing therefore slightly the usage of the known architecture (Figure 4). Does this mean that the SAaaS model will not respond to health care sensors to integrate data into the National Health Record? Absolutely not, for this to become a possible, there are some changes to be implemented in the usage of the SAaaS Cloud Infrastructure and new layers must be added into the PNHS patient records.

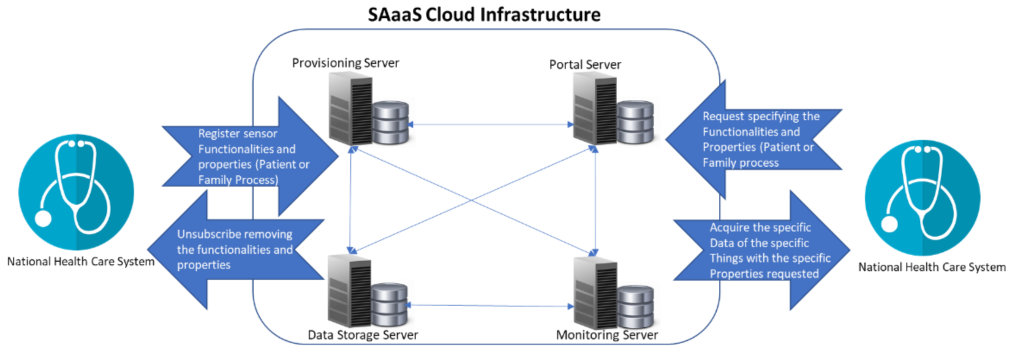

Figure 4 – New SAaaS Architecture Usage

The first change is that the sensor owners are the same as the data consumers, meaning that the National Health System will register the sensors into the cloud and retrieve their data, consuming all advantages this model have in processing, storing and effectiveness, responding to their needs in acquiring sensor data from elder patients without any initial investment on cloud infrastructures. There is no limitation regarding that a data consumer cannot be also a sensor provider, so that is a non-issue.

Another change here is to authenticate each sensor with his specific characteristics, functionalities and properties, adding the elder's national health process number, for the cloud to be able to respond and integrate on the PPDR. To respond to this need, another parameter may be inserted on the request, which is the type of sensor, their functionalities, and the process number of the national health system as a property needed for that sensor. Will this de-virtualize what the SAaaS model does, which is to create virtual sensors closer as possible according to the request needs? Absolutely not, the SAaaS model permits sensor owners to register their Things, and when they register, they must provide the sensor's functionality and their properties (ex. Functionality: Surveillance video camera, Properties: 40mpx, motion detection, etc.). Once on the registration, one of the properties must be the elder's health process number, so that when a request is made to address directly to that elder's sensor data, will bind to the sensor with the same property.

If that is guaranteed, the SAaaS model will respond creating the virtual sensors with the functionalities and properties inserted and there will be only the sensors directly related to the elders available, the one's previously registered with that same exact property, so that is also a non-issue.

What if the elder's have a set of sensors all with the same functionalities and properties? As an example, force sensors scattered around the house to determine if a fall occurs. The SAaaS model responds to that problem again directly without any change. The system will create virtual sensors grouping in a cluster the physical sensors with the same functionalities and properties and will respond to the consumer's request. Another way to guarantee the data access to the group of sensors is to discriminate distinct properties in each sensor and in each request, but there is no need for that. So, this is also a non-issue.

And if there is on the elder's home more than one elder and uses the same sensors? Here is the only problem that has no answer with the SAaaS model framework, the sensors will not differentiate which elder falls into the same home, it just knows it was a fall. In those cases, if there is more than one elder using the same sensors then the property inserted on the registration and request will have to be the FP and not the PPDR. In both cases, and depending on what sensor data will be retrieved, the alarms must be on the PPDR side, due to the distinct physiology each patient or elder have and what are the parameters range, that will trigger an alarm for the clinical staff to initiate the help protocol defined. This will be also a non-issue.

The flow will be as follows:

1. When the PNHS installs sensors to detect, determine elder's health parameters, daily routines, fall detection or any other Things intended for data retrieval, they must be register into the SAasS cloud infrastructure with the functionalities and properties of the sensor and adds a new property the PPDR or the FP, depending on if is a sensor regards one single elder or a group of elders.
2. The SAaaS cloud will register on the database the sensors with the functionalities and properties given.
3. On the consumer side the PNHS will request data specifying the same functionalities and properties that were register on the sensor, including the PPDR or the FP number.
4. The SAaaS cloud will search for the physical sensors that may respond to the needs expressed by the consumer side and will create virtual sensors with the same exact functionalities and properties given on the request.
5. The PNHS will acquire the specific data of the patient or family to be integrated on their databases.

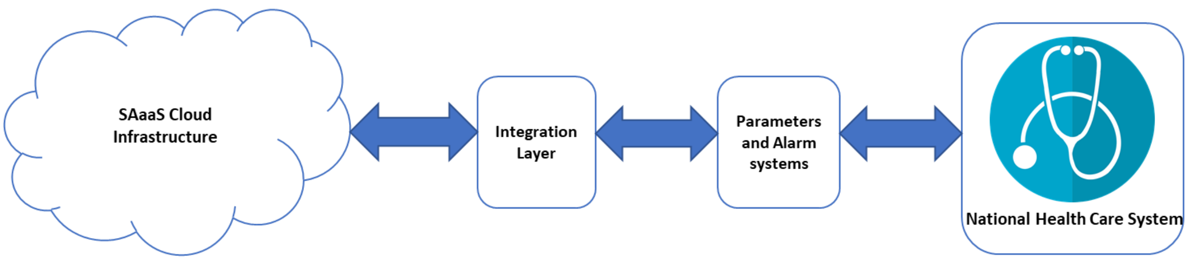

Figure 5 – Data Integration layers into the National Health Care System

On the other hand, a new integration layer must be created on the PPDR side to interact with the SAaaS system, retrieve the information and store it into the PPDR databases passing through an alarm check environment (Figure 5).

The integration layer is responsible for requesting and acquiring the data from the SAaaS cloud infrastructure, verify the information, and secure data and communications. Afterwards, the data follows to a second layer that verifies the parameters on the patient data record database and determines if there is an alarm to be triggered if the parameters read are outside the range of default parameters of that specific patient or if it will register the acquired data onto the PPDR database.

CONCLUSIONS

This preliminary study addresses the possibility to integrate sensor data gathered from elder's sensors with the specifications of the SAaaS framework using the potential of the cloud infrastructures for storing and processing capabilities and registering data into the patients records.

All features of the SAaaS were used to maintain possible the business model described on the paper, without changes, using the specifications the model provides, allowing health care systems to determine what sensors on elder's homes or wearable sensors to respond to elders needs and gather and register data into the health care databases.

This new framework design allows the registration of the sensors, the specific capabilities of a sensing cloud infrastructure, may register the gathered data into the Portuguese Nacional Health Patient Record, for all clinical and technical health staff to follow the elder's daily living and provide better care.

The limitation of this work depends entirely on the Portuguese National Health Patient Record connection with the framework and with the SAaaS infrastructure. Technologically everything is doable but depends entirely on if the National Health Authorities will allow the connection to the patients records.

For future research, the author pretends to implement the framework connected to the Portuguese National Health Patient Record, perform a study on an elderly care unit and register the sensors gathered data for the clinical and technical health staff to access remotely and be able to provide better health care to the elders.

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