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# Design of an IoT-Based Monitoring Sensor Network and Preliminary AI-Driven Data Analysis for Health Measurement in Residential Care Homes

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***Abstract*— Monitoring health and critical events in real time is crucial to ensuring well-being and enabling timely emergency response in Residential Care Homes. Despite the availability of numerous technological solutions, their application in real-life care environments remains limited. The Smart-RSA project addresses these challenges by developing an integrated, non-invasive Internet of Thing (IoT) monitoring system that combines environmental sensors, activity tracking technologies, and clinical-grade medical devices. Designed through a user-centered approach involving caregivers, healthcare professionals, and researchers, the system has the ambition to support four use cases: fall detection and prevention, nighttime monitoring, continuous vital signs and health monitoring, and, consequently, caregiver assistance. This paper presents the design methodology, IoT sensor network architecture, and a preliminary clinical data processing pipeline. A multilayer sensor infrastructure was deployed in a pilot facility, incorporating home automation devices, smart mattresses, RGB cameras, and health sensors for real-time monitoring. To assess the feasibility of health status classification, a stacked ensemble Machine Learning (ML) model (Random Forest, Decision Tree, Gradient Boosting) was trained and tested on the MIMIC-IV Emergency Department dataset, achieving an accuracy of 94.7%. These results validate the model's effectiveness in classifying clinical acuity levels based on vital signs. The Smart-RSA system has the potential to transform care delivery in long-term care facilities by enabling proactive, personalized, and data-driven care strategies.**

***Keywords—health monitoring, aging people, Residential Care Homes, Artificial Intelligence.***

## I. Introduction

The measurement and real-time monitoring of health and critical events is essential for effective emergency management in Residential Care Homes. The most common incidents among older residents are falls and unpredicted health events. These conditions not only pose significant health risks to the residents but also place a considerable burden on caregivers [1]. Nighttime represents a particularly vulnerable period in long-term care: falls among residents become more frequent and nurses presence is reduced. Moreover, approximately 40% of care homes residents with dementia experience disturbed sleep, which negatively affects their physical and psychological well-being while also disturbing co-residents and increase burden on caregivers [2]. This is often linked to a phenomenon known as sundowning: individuals with Alzheimer become more restless and confused as evening approaches and their vulnerability during the night increases [3]. In addition to resident-related risk factors, environmental conditions also play a significant role in the occurrence of critical events. Environmental disturbances such as poor lightning, noise and frequent care interruptions significantly impact the sleep quality of older people, thereby increasing the risk of accidents [4]. To address these challenges and to improve senior people's psychological and physical well-being, platforms leveraging Information and Communication Technologies (ICTs) and Internet of Things (IoT) solutions have been widely proposed [5]. These solutions often integrate wearable sensors, ambient monitoring systems and smart devices to monitor residents' activity and assess changes in behavioural patterns, necessary to detect and predict critical events such as falls or wandering. Wearable sensors are commonly used for the monitoring of activities and health status; however, this solution is often not suitable for senior people since they require active participation by the user [6][7]. Consequently, there is a preference for environmental sensors that can monitor both movement and environmental parameters in a non-intrusive manner. For instance, in the e-Vita project [8], environmental sensors as tags and passive infrared (PIR) motion sensors have been employed to monitor daily activities and detect anomalies in the behaviour of older adults living in multi-resident contexts, providing valuable data for early intervention and care planning. In the Healt@Home project [9], a domotic sensor network including PIR, a thermostat and sensors to detect switching on/off of lights has been employed to measure the well-being of older people in private home environments. In addition, classification of user health condition has been demonstrated in this project by the use of of non-invasive sensors for physiological measurements and Machine Learning (ML) techniques [10]. Environmental sensors also address the need to monitor elderly people during night hours: the study [11] proposes a textile-based pressure sensing matrix designed for integration into a smart bed mattress, enabling the characterization of a subject's sleep posture and movement, as well as the extraction of breathing patterns. Recent work has also explored the use of smart home technologies (SHTs) that combine sensing technologies and Artificial Intelligence (AI) to continuously monitor residents and detect abnormal patterns [12]. For example, in the ANCELIA project [13] an environmental optical sensor, enabled with a camera monitoring system, is used with AI to detect behavioural changes and prevent adverse events related to older people living in long-term care. In addition, recent literature highlights the evolution of these systems toward the concept of Supportive Smart Homes (SSHs), which go beyond basic automation to actively assist older adults and support active and healthy ageing [14]. However, while many of these solutions show technical feasibility, the majority of studies are confined to laboratory or pilot environments, which casts doubt on their reliability and safety in real-world scenarios. Moreover, there is a lack of risk indicators and monitoring protocols that are tailored to the specific characteristics of individual facilities, including their architectural constraints [15]. The Smart-RSA project - Ricerca e sviluppo per innovare le Marche - seeks to address these challenges by creating an integrated solution designed to improve the health monitoring and critical event management processes within nursing homes. Smart-RSA is built on multiple technological layers, incorporating advanced technologies for home automation and environmental management, alongside systems for monitoring the activities and clinical parameters of residents. This is further enhanced by ML-driven data analysis, enabling valuable insights to support care quality and facility management. This paper presents the methodology adopted for the sensor network definition and a preliminary clinical data processing analysis for the classification of resident's health status. The rest of this paper is organized as follows: Section 2 discusses the materials and methods including use cases definition and AI-driven data analysis; Section 3 presents the Sensor Network Configuration and ML Analysis; Section 4 reports the conclusions of the work.

## II. MATERIALS AND METHODS

### A. Pilot facility and Room Selection

The Smart-RSA project is being implemented in collaboration with "Il Picchio-Stella Polare", a cooperative that provides healthcare services across the territory of Ascoli Piceno (AP), with a particular focus on care for ageing people. The cooperative manages nursing and personal assistance at "Sanitas", a healthcare facility located in Castel di Lama (AP), catering to older individuals who are not completely self-sufficient and cannot be assisted at home. The "Sanitas" facility is divided into two floors, each hosting residents with different care needs:

- Protected Residence: designed for individuals who require some level of assistance with daily activities but can maintain a degree of independence.
- Residential Care Home: provides care for individuals who are partially or fully non-self-sufficient, requiring continuous medical care and comprehensive healthcare support.

Two rooms within the "Sanitas" facility have been selected for the Smart-RSA pilot. One room is in the Protected Residence, while the other is in the Residential Care Home. This selection provides the opportunity to test the system in different care settings, ensuring its flexibility and effectiveness in addressing a range of care needs.

### B. Methodology

This section outlines the methodology used to select and define environmental, activity, and vital sign monitoring sensors, ensuring alignment with both clinical needs and operational constraints. A qualitative methodology, including focus group analysis and use cases definition, has been conducted. This approach began with a co-design session involving various stakeholders, including researchers, caregivers, and healthcare experts. Site visits to the "Sanitas" facility were conducted to understand the specific needs of the residents and caregivers and to assess the physical spaces where the sensor network will be installed. Based on these discussions, four primary use cases emerged (Fig.1):

- The first use case focuses on risk assessment and detection of eventual incidents as falls. The system must be designed to promptly send alerts if an incident occurs and to predict fall risks in advance using AI and ML techniques. This can be achieved through activity monitoring using non-intrusive motion sensors and

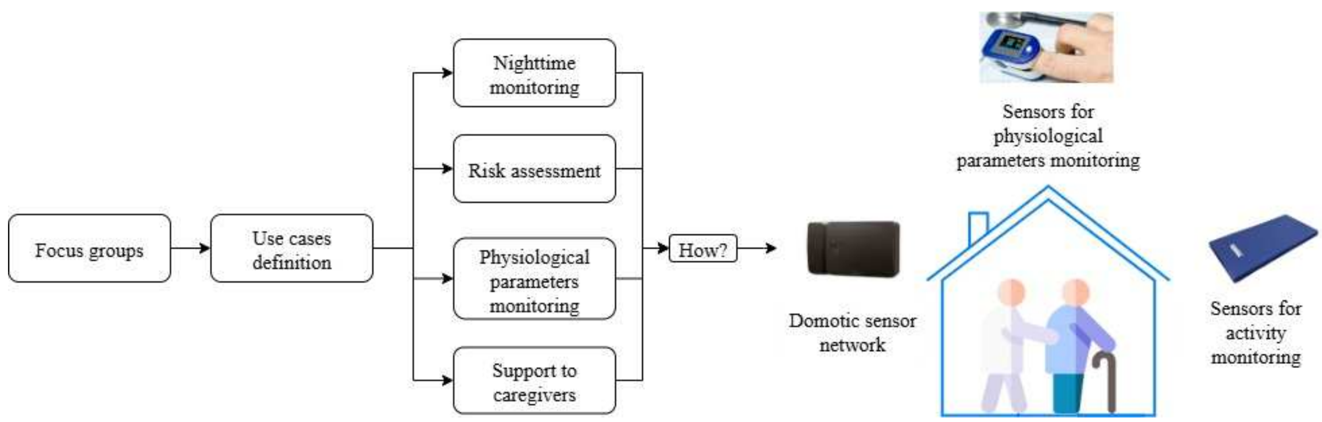


*Fig. 1. Workflow of use cases definition.*

domotic sensors, which do not require the active participation of the resident, alongside wearable sensors equipped with accelerometers and gyroscopes, that provide an additional layer of monitoring.

- Another critical need identified was the ability to monitor older people during the night, particularly those with cognitive impairments. The system should be capable of notifying caregivers instantly if a resident gets up and leaves their room. Monitoring the quality of the residents' sleep is essential also because sleep patterns can significantly impact daily activities and overall well-being.

- A third use case involves the continuous monitoring of health parameters such as heart rate, respiratory rate, blood pressure, and oxygen saturation, which are key indicators for early detection of clinical deterioration in older adults. By integrating wearable and unobtrusive biosensors into the monitoring system, real-time physiological data can support timely interventions and personalized care. When combined with AI-based analytics, these data help reveal subtle anomalies not easily detected by caregivers, improving preventive care.

- Lastly, there was a clear need to provide caregivers with meaningful support in performing their daily tasks. A system that offers real-time monitoring of older people can assist caregivers in providing more effective and tailored care.

In addition to the technical and operational aspects, the focus group analysis also addressed ethical considerations related to data privacy and the use of monitoring technologies in care settings. As a result, the system design and data management processes were aligned with key regulatory frameworks, including the EU Medical Device Regulation (MDR 2017/745) [16] for the use of clinical-grade sensors, the General Data Protection Regulation (GDPR) [17] for the secure storage and processing of personal health information, and ISO 13485 [18] standards for the integration of quality-managed medical devices. These measures were incorporated from the early stages of the project to ensure compliance and build trust among caregivers, residents, and administrators.

### C. *Sensors network evaluation*

To implement the monitoring system within the selected rooms at the "Sanitas" facility, a variety of sensors were evaluated to address the identified use cases. The system needs to rely on a fully non-invasive sensor network, specifically designed to ensure continuous monitoring without disrupting the daily life or comfort of the residents. Sensor selection was identified on multiple evaluation criteria, including accuracy (precision in detecting target events such as falls), non-invasiveness (minimal physical or psychological disruption), reliability (robust performance in real-world conditions), cost-effectiveness (alignment with budget constraints), and integration capability. The sensor infrastructure was organized into three categories, each contributing uniquely to the objectives of the project and supporting different aspects of resident care and safety:

- Home automation sensors: they play a fundamental role in detecting changes in the environment or in the interaction of the residents with the surroundings.

- Activity monitoring sensors: This category includes devices aimed at continuously monitoring the residents' behaviour and movements in a non-invasive manner, with a focus on detecting falls and nighttime activity.

- Sensors for physiological parameters: the sensor network includes medical devices to acquire clinical data and provide continuous or periodic measurements that support a clinical risk assessment.

### D. *System Architecture*

The system architecture of the Smart-RSA project integrates different Internet of Things (IoT) sensors for activity monitoring, physiological tracking, and home automation, to enhance both the care of old residents and the management of nursing home facilities. The data generated by the IoT devices will be securely stored on Google Cloud Platform (GCP) and processed using a MySQL relational database for efficient management. A user-friendly dashboard developed using Grafana (https://grafana.com/), will allow caregivers and facility staff to monitor the health and well-being of the residents in real-time. This integration of technologies will improve operational efficiency, enhance safety and comfort, and enable the delivery of high-quality personalized care.

### E. *Data Flow Use Case: Vital Parameters Monitoring*

This section details the clinical data processing pipeline for vital parameter monitoring within Smart-RSA. The workflow transforms raw physiological data into actionable clinical intelligence through systematic computational methods. The model is intended to classify the health status of the residents. While awaiting the installation of sensors and data collection at the "Sanitas" facility, the clinical data processing pipeline has been preliminarily tested using the MIMIC-IV- Emergency Department (ED) dataset [19].

*Dataset description:* MIMIC-IV-ED is a publicly available, de-identified clinical database derived from a Medical Center in Boston, spanning the period 2011–2019. It includes detailed information on patient encounters in the emergency department, capturing triage data, vital signs, chief complaints, procedures, lab results, and discharge outcomes.

The collected data underwent strict de-identification protocols to ensure patient privacy. The access to the dataset was granted following completion of the Collaborative Institutional Training Interactive (CITI) Program's Human Research [20] by one of the authors.

*Pre-processing phase and Feature Engineering:* Preprocessing began by selecting patients with at least two vital sign measurements to ensure temporal reliability. The dataset was then filtered into two cohorts: elderly patients (age $\geqslant 65$) and a general population group. Six core vital parameters, body temperature, heart rate, respiratory rate, oxygen saturation, systolic blood pressure, and diastolic blood pressure, serve as foundational features. Patient-specific cleaning eliminates physiologically implausible values while preserving clinical relevance. This stage reduces dataset dimensionality while preserving the majority of clinically actionable records. The final dataset included vital signs as input features and Emergency Severity Index (ESI) as the target variable. The ESI is a number ranging from 1 to 5 assigned during the triage phase in an Emergency Room and describes the level of severity (acuity), where 1 indicates the highest severity and 5 indicates the lowest severity.

*Model deployment:* The model used for health status classification is a stacked ensemble model combining Random Forest, Decision Tree and Gradient Boosting [21]. The model has been supervised taking in consideration the ESI numbers assigned to each person during the triage. The model has been trained using 80% of data and tested on the other 20%. To evaluate the performance of the algorithm, the following metrics has been computed: accuracy (Equation 1), precision (Equation 2), recall (Equation 3) and F1-score (Equation 4).

$$Accuracy\ [\%] = \left(\frac{(TP+TN)}{(TP+FP+FP+FN)}\right) * 100 \quad (1)$$

$$Precision\ [\%] = \frac{TP}{TP+FP} * 100 \quad (2)$$

$$Recall\ [\%] = \frac{TP}{TP+FN} * 100 \quad (3)$$

$$F1Score\ [\%] = \frac{2*Precision*Recall}{Precision+Recall} * 100 \quad (4)$$

where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative. In our case, precision, recall, and F1-score were computed using the weighted average approach, which accounts for class imbalance.

## III. SENSOR NETWORK CONFIGURATION AND ML ANALYSIS

This chapter presents the outcomes derived from the sensor network configuration, as defined in the methodological section, and from the subsequent analysis performed using ML techniques. The focus is on evaluating the system's capacity to monitor relevant parameters and generate meaningful insights through ML-driven data processing.

### A. *Sensor network configuration*

As part of the sensor setup, a specific classification has been adopted to better structure the monitoring framework. Sensors have been grouped into three main categories and Table I provides the technical characteristics of the selected sensors and devices.

**Home automation sensors**, which monitor environmental conditions and user interactions with the domestic space; The DOMUS multi-sensor monitors ambient parameters such as temperature, humidity, light, and motion. It enables real-time detection of inactivity, environmental anomalies, or unusual movement patterns, which can be indicative of risk situations, such as a fall or prolonged immobility. The MICRO POLI magnetic contact sensor detects the opening and closing of doors and windows and includes an accelerometer to identify vibration or inclination. This sensor is particularly useful in preventing wandering episodes, especially during the night. A NEBULA stand-alone smoke detector ensures fire safety by detecting the presence of smoke and emitting an acoustic alarm. The UNUM-X DT X5 is a dual-technology motion detector (PIR and microwave) capable of detecting occupancy with high reliability, even in low-light conditions. It enhances real-time presence detection, supporting fall detection and movement monitoring if outcomes are analysed with AI techniques. Finally, the VOLO proximity reader uses RFID technology (13.56 MHz) to manage access control. The chosen home automation sensors are produced by Ksenia Security.

**Activity monitoring sensors**, aimed at detecting movements, gestures, and behavioral patterns; To monitor movements and sleep patterns during the night, the smart mattress WhizPad, shown in Fig.2, has been selected. WhizPad [22] is a thin mattress pad made of memory foam and conductive textile materials arranged in a sandwich structure. The layer of foam contains a sensing film composed by 30 piezoresistive sensors organized in a 6x5 matrix. The operating principle of WhizPad is similar to that of a membrane switch, which controls the activation and deactivation of a circuit. When no pressure is applied to the WhizPad, the top and bottom layers remain separated, resulting in an open circuit. When pressure is applied, the layers come into contact, closing the circuit. The pressure signals collected by WhizPad can be used to detect events as presence on bed, sleep posture, sleep quality, and movement counts. Other devices selected for activity monitoring are RGB cameras, which represent a reference for the other sensors. In particular, the selected camera is the C920 HD Pro Webcam from Logitech. RGB cameras, used in combination with advanced Deep Learning (DL) as Convolutional Neural Networks (CNNs), are able to detect patterns and features associated with fall incidents [23], [24].

**Sensors for physiological parameters**, which gather vital signs and biometric data relevant to the user's health status; Among the physiological parameters considered most relevant in residential care settings are heart rate, blood pressure, oxygen saturation, and body temperature. Electrocardiogram (ECG) sensors are used to monitor heart rate (HR) and Heart Rate Variability (HRV), supporting the identification of cardiac anomalies such as arrhythmias or signs of cardiovascular stress, which may correlate with fall risk or sudden health decline. Pulse oximeters enable the real-time measurement of oxygen saturation ($SpO_2$) and pulse rate, allowing caregivers to detect early signs of respiratory impairment, especially important in frail or cognitively impaired residents who may not verbalize symptoms. In addition, body temperature sensors are used to track potential febrile conditions, aiding in the early detection of infections or inflammatory responses. The Electrocardiograph selected for the system is the PCECG- 500 by Lepu Medical. For the measurement of blood pressure, $SpO_2$, temperature and glycemia, the device PC-300 spot-check monitor by Gima has been chosen.

*Fig 2. WhizPad smart mattress.*

*Table 1 Technical specification of the selected sensors*

| **Sensor** | **Measured parameters** | **Technical specifications** |
|---|---|---|
| Multifunction sensor DOMUS | Temperature<br>Humidity<br>Movement<br>Light intensity | Temperature precision: ± 0,5°C<br>Temperature resolution: ± 0,1°C<br>Humidity precision ± 0,5% RH<br>Humidity resolution: ± 2%RH<br>PIR sensor range: 6 m, 45 ° angle |
| Magnetic and inertial sensor MICROPOLI | Door/window opening<br>Door/window vibration | Operating temperature: from + 5°C to + 40 °C |
| Smoke detector NEBULA | Smoke detection | Operating temperature: from -10 °C to +60 °C |
| PIR sensor UNUM-X DT X5 WLS | Presence | PIR sensor range: 12 m, 85 ° angle (WIDE), 18 m, 5° (NARROW) |
| Outdoor proximity sensor VOLO | Presence detection | Technology: RFID 13.56 MHz |
| WhizPad smart mattress | Pressure applied | Sensing range: 1800 N/$m^2$ - 4300 N/$m^2$ |
| C920 HD Pro Webcam | RGC images and videos | dFoV: 78 °<br>Resolution: 1080 p/30 fps - 720p/30 fps |
| PCECG-500 | ECG | HR measuring range: 30 bpm – 300 bpm<br>HR precision: ± 1 bpm<br>Accuracy: ± 5% |
| PC-300 spot-check monitor | ECG, blood pressure, $SpO_2$, temperature and glycemia | Accuracy blood pressure (max. mean difference): ± 5 mmHg<br>$SpO_2$ accuracy: ± 3 % (for $SpO_2$ between 70% - 100%)<br>Temperature accuracy: ± 0.2 °C (for temperature between 36 °C- 39 °C)<br>ECG accuracy: ± 2% |

## B. ML analysis

Since the installation of the monitoring system is currently ongoing, the MIMIC-IV-ED publicly available dataset was identified and used to define and test a preliminary ML-based data analysis methodology. This allowed for the development and initial validation of the proposed analytical framework in the absence of real-world data from the pilot installations.

For health status classification across five acuity levels (as defined by the Emergency Severity Index), the model achieved an accuracy of 94.7%, a weighted average precision of 94.6 %, a weighted average recall of 94.7% and a weighted average F1-score of 94.6%. These metrics reflect robust and reliable classification performance on a large support set of over 31,000 samples. Overall, the results validate the effectiveness of the model in classification tasks within clinical settings.

# IV. Conclusion

This paper presented the preliminary design and development phases of the Smart-RSA project, an integrated system for real-time monitoring and risk assessment in Residential Care Homes. The project combines environmental sensing, activity monitoring, and physiological parameters acquisition into a multi-layered, non-invasive technological infrastructure. Through a user-centered design process, four core use cases that guided the selection of a tailored sensor network were defined: fall detection and prevention, nighttime monitoring of residents, continuous clinical parameters monitoring and caregiver support. Preliminary validation of the clinical data processing pipeline, performed using the MIMIC-IV-ED dataset, demonstrated promising results: the stacked ensemble model for health status classification achieved high performance metrics across a large and diverse dataset. These findings confirm the feasibility of the approach in supporting risk assessment, health monitoring, and personalized care in real-world settings. Future developments of the Smart-RSA project will follow a structured roadmap. The first step will be to complete the installation of the sensor network in the selected rooms at the “Sanitas” facility. Once the hardware infrastructure is in place, the next objective will be to finalize the data integration process, ensuring that all information from the various sensors flows into a centralized database. Following this, the clinical classification algorithm—previously tested on the MIMIC-IV-ED dataset—will be applied to the real-world clinical data collected within the facility. Finally, the project will focus on developing additional ML models capable of analyzing data coming from home automation sensors and activity monitoring devices. These models will be integrated with clinical insights to provide a more comprehensive and personalized picture of each resident’s health status, ultimately supporting proactive and data-driven care.

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