A Bluetooth Proximity-Based IoT Approach for Continuous Monitoring of Indoor Sedentariness

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***Abstract*—Sedentary behavior is a critical factor influencing overall health and well-being, particularly in aging populations. This work presents an indoor monitoring solution leveraging Bluetooth-based proximity estimation to infer users' location and movement patterns across different home environments. The objective is to generate a Sedentary Behavior Index (SBI) that quantifies the duration individuals spend in specific domestic spaces without requiring active user input. This index, derived through passive and pervasive sensing, provides healthcare professionals and researchers with insights into users' lifestyle and activity levels within the context of their daily living environment. The proposed system, deployed in 45 houses, monitors 55 users and operates as a proximity-based IoT service that seamlessly integrates with broader health monitoring studies, enabling context-aware analysis when cross-referenced with clinical outcomes or other observational data. This approach aims to support continuous, unobtrusive, and personalized well-being assessments, laying the groundwork for adaptive interventions in remote healthcare and aging-in-place scenarios.**

***Index Terms*—IoT, Bluetooth, Sedentariness, Proximity detection**

I. Introduction

Sedentary behavior, defined as any waking activity characterized by an energy expenditure less than 1.5 Metabolic Equivalent of Tasks (METs), has emerged as a significant risk factor for a broad spectrum of adverse health outcomes. These include cardiovascular disease, type 2 diabetes, musculoskeletal impairments, obesity, and even premature mortality [1]. The detrimental impact of sedentariness is especially pronounced among older adults, for whom prolonged inactivity is often correlated with increased frailty, diminished functional capacity, cognitive decline, and reduced quality of life. Consequently, the identification and quantification of sedentary behavior in free-living conditions has become a key research and clinical objective in the context of preventive healthcare, ageing-in-place strategies, and personalized medicine. Traditional methods for assessing sedentariness typically involve self-reported questionnaires or the use of wearable devices such as accelerometers and fitness trackers. While these tools provide valuable insights, they are not without limitations. Self-report methods are inherently subjective and susceptible to recall bias, while wearables, although objective, often require continuous user compliance and may introduce discomfort or stigmatization, particularly in older adults populations. Moreover, these approaches frequently fail to capture the spatial and contextual dimensions of inactivity, such as where and how sedentary behavior occurs within the home environment, which are essential for tailoring interventions and understanding lifestyle patterns in detail.

Recent advances in ambient sensing, pervasive computing, and Internet of Things (IoT) technologies offer promising opportunities to overcome these limitations. In particular, Bluetooth Low Energy (BLE) proximity sensing enables unobtrusive monitoring of user presence and movement across different indoor zones by leveraging signal strength patterns and spatial anchors such as fixed beacons [2]–[5]. This infrastructure, already integrated into many consumer devices and easily deployable in residential settings, provides a low-cost, energy-efficient, and privacy-preserving solution for continuous behavioral monitoring [6].

This work proposes a novel BLE-based IoT framework for passive, continuous, and context-aware monitoring of indoor sedentariness. By inferring user location and transitions across domestic spaces, the system computes a Sedentary Behavior Index (SBI), which quantifies time spent in low-mobility conditions without requiring explicit user interaction [7]. The SBI is designed as a composite metric that integrates spatial, temporal, and behavioral features, such as room occupancy duration, frequency of inter-room transitions, and time spent outside the home, to produce a granular profile of sedentary patterns.

Developed within the framework of the ongoing Tuscany Health Ecosystem (THE) project, the proposed system aligns with broader digital health initiatives aimed at enhancing home-based care, supporting clinical decision-making, and promoting healthy aging. It is worth noting that the system is intended to complement, not replace, other forms of analysis to gain a holistic view of the user's well-being. It provides healthcare professionals and researchers with actionable, high-resolution data that can be cross-referenced with clinical assessments, observational studies, or intervention outcomes. This work contributes to the development of scalable, user-friendly tools for early detection of sedentary risk, adaptive intervention design, and personalized well-being support in real-world settings.

II. Related Work

The application of BLE technology in monitoring physical activity levels, particularly among older adults, has gained

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significant attention due to its capability for proximity sensing in indoor environments [8], [9]. This technology leverages Received Signal Strength Indicators (RSSI) to determine close-contact interactions and space occupation. Multiple systems have been proposed in the literature to enhance the accuracy and reliability of indoor activity tracking through BLE beacons, particularly focusing on the older adults demographic, whose health is often intrinsically linked to mobility and activity levels. This context is addressed in multiple studies that explore the behavioral patterns and physical interactions of seniors, leveraging proximity data captured through BLE devices. For instance, the work in [10] demonstrate the utility of Bluetooth proximity sensing in discerning time spent by individuals in various office and nursing environments, laying the groundwork for using similar methodologies to quantify activity levels of older users. By correlating proximity sensing with daily activity, the study provides crucial insights into how such technologies can inform interventions aimed at reducing sedentary lifestyles among older adults.

The functionality of BLE for proximity sensing is also well captured in various methodological explorations of distance estimation techniques, where accuracy is tightly bound to the algorithms employed in interpreting RSSI values. The work in [11] shows a Bluetooth-based contact tracing architecture that showcases different methodologies pertinent to accurately capturing proximity data in critical environments like health-care settings . These advancements in architecture design are critical in ensuring that systems developed for computing sedentariness indices also maintain utility in monitoring and promoting better health outcomes.

In addition to academic exploration, practical implementations of BLE technology for detecting human movement dynamics have shown promising results. In [12], the authors focus on workplace interactions captured through BLE, demonstrating that real-world deployments can yield profound insights for environmental designs that foster decreased sedentariness among employees, a principle readily extensible to older adults user settings.

In [13], a BLE-based system specifically designed to monitor wandering behavior in individuals with dementia has been evaluated in a long-term care setting. Early results showed the system could detect repetitive movement patterns and support real-world automatic wandering detection.

To explore ways of assessing daily living activities linked to independence and health, the authors in [14] examined the effectiveness of BLE beacons in accurately distinguishing lifestyle events within a home. Their study also demonstrated that these devices offer practical feasibility thanks to their interoperability, flexibility, and low maintenance needs.

In summary, the literature surrounding BLE technologies for sedentary behavior measurement among the older adults, highlights a confluence of innovative methodologies [4], practical deployments [2], real-world datasets [3], and the necessity of context-sensitive designs [7]. The integration of advanced algorithms that enhance signal interpretation, privacy considerations in data handling, and practical insights from existing deployments form the intricate tapestry of the research landscape. As future studies continue to explore the intersection of Bluetooth technology and health monitoring, the accumulated evidence will surely serve as benchmarks for developing robust systems [15], aimed at reducing sedentariness and improving the quality of life among older adults.

III. Proposed System

In this section, we outline the architecture of the proposed system, describing both the hardware devices deployed and the software services used to collect, process, and analyze proximity data. We further explain how the system was installed and tested in real-world home environments, introducing the monitoring platform designed to track, assess, and visualize the system activity.

A. Architecture

The system is designed to unobtrusively monitor the movements of older adults within their homes in order to estimate their sedentariness, which is an important indicator of health and well-being. It relies on BLE technology to determine which rooms the user spends time in, enabling room-level localization without requiring cameras or intrusive sensors.

Each monitored user wears a small BLE tag, the MineW T3 model powered with a coin battery (Fig. 1a), typically mounted on the watch strap by means of a silicon case, which periodically broadcasts beacon messages containing a unique identifier. These beacons are transmitted at a fixed interval, about every second, ensuring that the system has frequent updates on the user's proximity.

(a) (b)

Fig. 1: (a) Bluetooth tag on the left side encapsulated within a silicon box and (b) Bluetooth gateway plugged to an USB adapter.

In the home, BLE gateways equipped with receivers are installed in key rooms, selected together with the user, such as the bedroom, kitchen, and living room. These gateways, based on the MineW MG3 model, are powered with an USB adapter plugged to the power line and continuously scan for BLE beacons emitted by the user's tag (Fig. 1b). When a beacon is detected, the gateway records the beacon's signal strength (RSSI), the time of reception, and the unique ID of the tag. This information is essential for accurately estimating the user's location within the house.

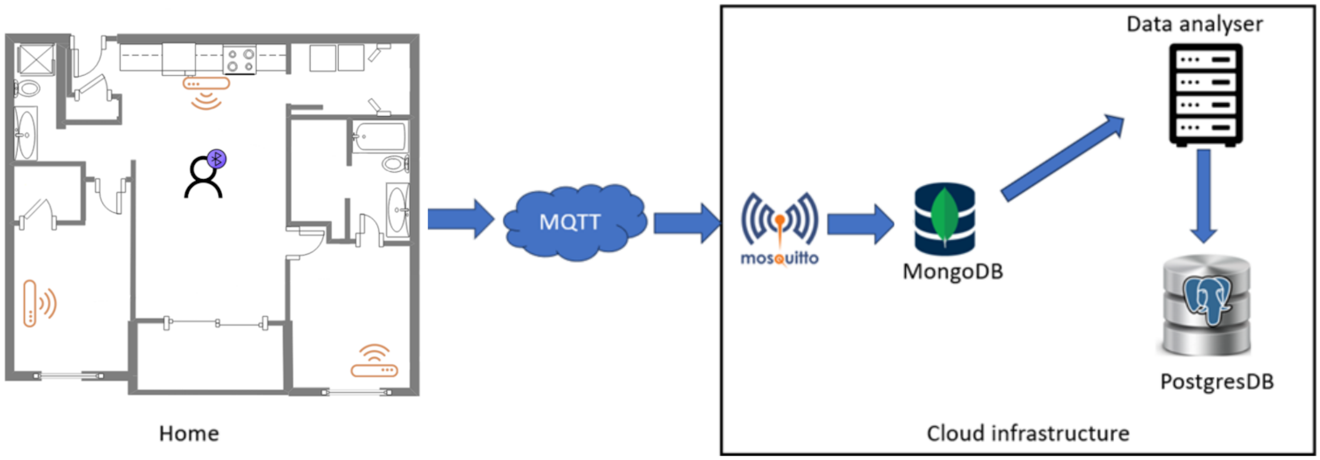


Fig. 2: Overall system architecture depicting its main components and the data flow.

Each gateway is connected to the local home's Wi-Fi network. After receiving a beacon, the gateway packages the relevant data, including the tag identifier, RSSI, timestamp, and the gateway's own identifier, and transmits it to a central server using the MQTT protocol as shown in Fig. 2. MQTT is a lightweight, publish/subscribe messaging system that is well suited to Internet of Things (IoT) applications, as it ensures efficient and reliable delivery of messages even over networks with variable connectivity. The central server aggregates the data coming from all the gateways storing it in a MongoDB database. To ensure privacy and security, all data are transmitted over encrypted connections, each user is assigned a random identifier, personal information is never transmitted, and beacon and gateway addresses are stored in the database in an anonymized format. A processing module, called Data Analyser, runs periodically and analyzes the RSSI measurements to estimate which room the user is most likely in at any given moment. The Data Analyser is implemented as a Java-based application that performs three main operations for each user configured in the system. First, it retrieves the raw data collected over the previous 24 hours. This retrieval process is scheduled to run automatically once per day during the night, ensuring that all data generated by the user's wearable tag and received by the gateways is consolidated without impacting system performance during active hours.

Second, the analyzer processes the raw data to determine the visited room for every minute of the day. This is achieved through a proximity detection algorithm, which aggregates beacon data in one-minute intervals and estimates the most likely room based on the RSSI values from the gateways. Specifically, the algorithm uses two key conditions. The first condition requires that at least 20% of expected beacon messages from the user's tag must be received, from each gateway, during each one-minute window of aggregated data; this ensures that the estimation is based on sufficient signal samples. The second condition involves computing the median RSSI value for each gateway within the aggregation window. The visited room is then determined as the location corresponding to the gateway with the highest median RSSI value, which indicates the strongest signal and, therefore, the closest proximity.

Using the computed room occupancy data, the service can then calculate a Sedentary Behavior Index in order to offer to the caregivers a valuable and comprehensive tool to help assessing users' overall condition. The details of the algorithm designed to calculate the user SBI are described in section IV.

B. Test and Deployment

Before deploying the system in the actual experimental campaign, we conducted preliminary tests to verify the stability and robustness of the architecture, as well as to validate the installation process, by setting up the system in a controlled testbed environment. The installation kit comprises:

- 5 gateways positioned in the kitchen, bathroom, sleeping room, living room, entrance
- 1 tag assigned to the user

The user accepted wearing the beacon on the wrist to mimic the behavior of the actual enrolled users. The installation required about 1 hour to configure and to deploy the 5 gateways and to set up the tag. Data was collected over a two-month period, during which we gathered more than 32 million beacon messages.

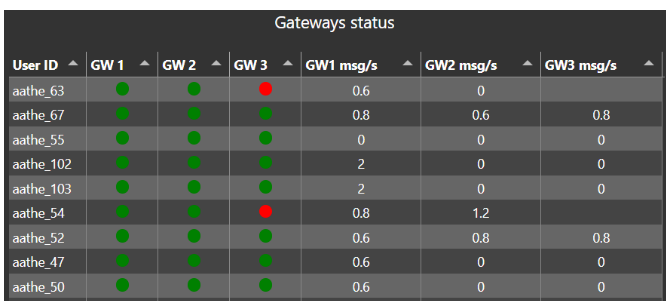
Following the testbed phase, and once the selected users had enrolled for the project, the pilot sites were organized and deployed in two successive rounds. During each round, we deployed the full system at the user's premises. A total of 55 subjects were enrolled in the study (mean age $\pm$ SD: 74 $\pm$ 4.6 years), of whom 68% were women and 32% were men. The life-cycle of the pilot site can be summarized with the following steps:

1) **Activation Phase:** this phase involves configuring the installation kit for a specific user. In particular, we

recorded the anonymized user ID along with the unique identifiers associated with the Bluetooth tag and the three gateways

2) **Deployment Phase:** this phase requires scheduling a home visit with the user to install the system. The installation typically takes between 30 minutes and 1 hour. Together with the user, we identify the optimal locations for placing the gateways. We also provide a detailed explanation of the components included in the installation kit, supported by a dedicated user manual
3) **Test Phase:** after installation, we verify that the hardware is functioning correctly. A custom dashboard is used to periodically monitor the system and quickly detect any anomalies
4) **Monitoring Phase:** during this phase, the user is monitored over a predefined period (e.g., 6 months). Data is automatically collected from the gateways, and the back-end system processes it to compute relevant statistics
5) **Deactivation Phase:** this final phase involves removing the installation kit and sanitizing all components to ensure they can be reused for another user

To ensure the correct functioning of the system and support effective monitoring, several dedicated tools were developed. The first tool is a real-time dashboard that displays the current status of all the deployed devices (Fig. 3). It shows the connection status of each gateway, indicating whether a device is online, experiencing issues, or offline, along with the rate at which each gateway is receiving beacon messages. This enables quick identification of connectivity problems or unexpected drops in data transmission.



Gateways status

User ID	GW 1	GW 2	GW 3	GW1 msg/s	GW2 msg/s	GW3 msg/s
aathe_63	●	●	●	0.6	0	
aathe_67	●	●	●	0.8	0.6	0.8
aathe_55	●	●	●	0	0	0
aathe_102	●	●	●	2	0	0
aathe_103	●	●	●	2	0	0
aathe_54	●	●	●	0.8	1.2	
aathe_52	●	●	●	0.6	0.8	0.8
aathe_47	●	●	●	0.6	0	0
aathe_50	●	●	●	0.6	0	0

Fig. 3: Dashboard showing the real-time gateways status and message speed.

The second dashboard (Fig. 4), is designed to visually support the analysis of user habits by representing room occupancy across sequences of days. By displaying patterns of room usage in an intuitive format, this tool helps highlight behavioral routines or changes that may indicate evolving health conditions or shifts in daily activity.

The third tool (Fig. 5), based on the Grafana platform, provides a historical overview of system activity by presenting past data for all monitored users. This dashboard allows operators and researchers to quickly review trends and identify anomalies over time, offering a comprehensive snapshot of system performance and user movement patterns at a glance.

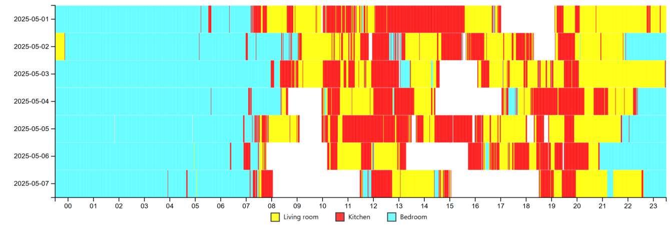


Fig. 4: Dashboard showing a user's habit by plotting the room utilization during several days.

Finally, to provide users feedback on the collected data, we designed a dashboard accessible through a mobile app developed specifically for the project. This dashboard allows users to view their room occupancy patterns over the past seven days (Fig. 6).

IV. Sedentary Behavior Index

Sedentary behavior, particularly in older adults, is strongly associated with adverse health outcomes including functional decline, frailty, increased fall risk, and worsening of chronic conditions such as hypertension and type 2 diabetes. Prolonged periods of inactivity within domestic spaces can be an early marker of reduced physical function or social disengagement. Therefore, passive and continuous monitoring of indoor behavior can support early detection and intervention strategies in aging-in-place scenarios.

The *Sedentary Behavior Index* (SBI) is designed to provide a clinically meaningful, context-aware metric that quantifies individual sedentary patterns over time. Unlike wearable-dependent solutions, our approach leverages Bluetooth proximity-based localization to infer room occupancy duration, and user mobility within the home environment.
The SBI is a composite score in the range $[0, 1]$, where 0 denotes high mobility (low sedentariness) and 1 represents critical sedentary behavior. It is computed daily from three primary indicators:

1) **Time Spent in Rooms (P)**
A weighted distribution of time spent in each room, where weights reflect the clinical relevance of sedentariness in specific spaces (e.g., staying in the bedroom during the day is more sedentary than being in the kitchen). Let roomTime_i be the time spent in room i, W_i its weight, and T the total monitored time. The normalized weighted sedentary presence is:

$$P = \sum_{i=1}^{N} \left(\frac{\text{roomTime}_i}{T} \cdot W_i \right)$$

2) **Number of Room Transitions (T)**
This represents intra-home mobility. The normalized

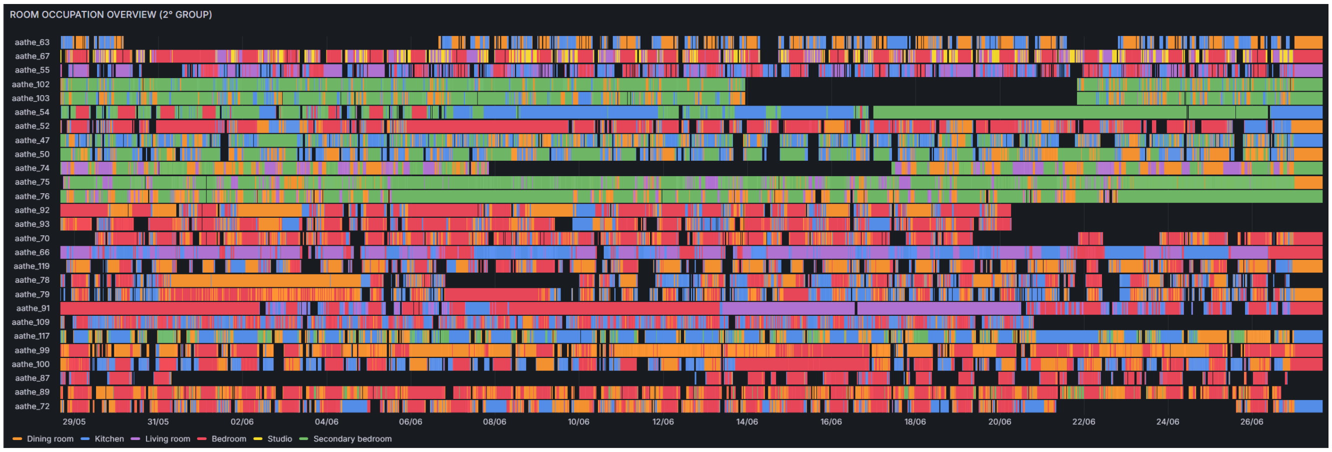


Fig. 5: Historical data dashboard based on the Grafana platform.

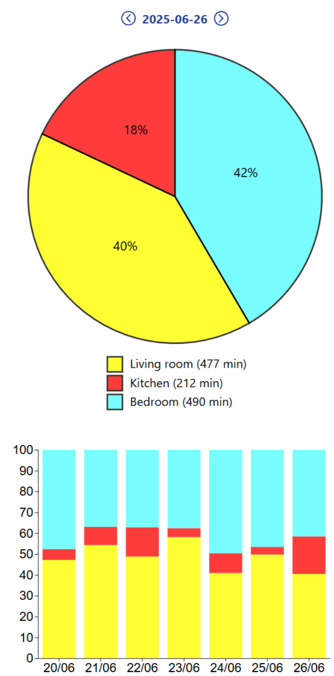


Fig. 6: Screenshot of the charts shown on the user's app.

value is calculated by comparing actual transitions to an expected baseline:

$$T_{\text{norm}} = 1 - \min\left(\frac{\text{actual transitions}}{\text{expected transitions}}, 1\right)$$

3) **Time Spent Outside (O)**
The proportion of daily active time spent outside the home is inversely correlated with sedentariness:

$$O_{\text{norm}} = 1 - \min\left(\frac{\text{time outside}}{T}, 1\right)$$

These components are combined linearly with tunable weights α, β, and γ:

$$\text{SBI} = \alpha \cdot P + \beta \cdot T_{\text{norm}} + \gamma \cdot O_{\text{norm}}$$

The rationale behind this algorithm lies in balancing clinical interpretability, computational efficiency, and unobtrusive data acquisition. Not all inactivity is equal: prolonged time in bed during waking hours may signal greater concern than time in the living room. Low transition counts reflect restricted mobility, and time spent outside often correlates with better functional health. This formulation enables the SBI to serve as a digital biomarker for daily behavior, suitable for long-term monitoring tools. It supports trend analysis, real-time alerts, and adaptive care planning within personalized health ecosystems.

Figure 7 provides a high-level schematic of the SBI computation pipeline. The system collects room occupancy data via Bluetooth-based proximity estimation. This is processed to extract three behavioral indicators: presence in sedentary-prone rooms, number of room transitions, and time spent outside the home. Each component is normalized and weighted to compute the final SBI score.

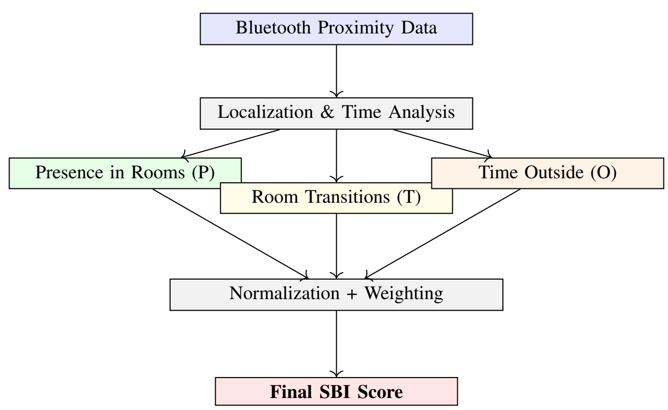


Fig. 7: Schematic of the Sedentary Behavior Index (SBI) computation pipeline.

The SBI computation relies on configurable weights for each component and on room-specific sedentary weighting. Table I summarizes these default parameters, which may be adjusted based on individual profiles or clinical priorities.

Parameter	Default Value
Weight for presence (P) – α	0.5
Weight for transitions (T) – β	0.3
Weight for outside time (O) – γ	0.2
Expected transitions per day	15
Max normalized outside time	4 hours
Room weight: Bedroom	1.0
Room weight: Living Room	0.7
Room weight: Kitchen	0.4
Room weight: Bathroom	0.2

TABLE I: Default weights and thresholds for SBI calculation (tunable).

For individuals aged $\geq$ 65, we propose to stratify the SBI score into four risk categories, enabling personalized health monitoring: Active, Moderately Active, Sedentary, and Critically Sedentary. Table II reports the four risk categories together with the SBI range thresholds and the corresponding interpretation.

SBI Range	Risk Category	Interpretation
0.00–0.25	Active	Healthy mobility patterns
0.26–0.50	Moderately Active	Some sedentary episodes, but not clinically concerning
0.51–0.75	Sedentary	Prolonged periods of low mobility; potential early intervention
0.76–1.00	Critically Sedentary	High risk of decline; requires clinical follow-up or intervention

TABLE II: SBI risk categories and interpretation for older adults (65+).

These thresholds are derived from empirical evidence in the conducted preliminary test, and should be adaptable to individual baselines or trends. The final validation of the proposed index will be conducted at the conclusion of the experiments, based on additional clinical indicators obtained from healthcare specialists.

V. Conclusion

Monitoring daily activity levels in older adults is essential for assessing their health, independence, and risk of functional decline. This work presents a Bluetooth-based proximity detection system designed to unobtrusively monitor the movements of older adults within their homes. By enabling room-level localization through wearable BLE tags and fixed gateways, the system provides continuous data on user presence and movement patterns without compromising privacy or requiring complex infrastructure. This information allows for the calculation of a sedentariness index, offering valuable insights into daily activity levels that can support health evaluation and early intervention. Although the system is deployed in an ongoing project and the results are therefore not yet complete, at the end of the experimental campaign, we plan to comprehensively evaluate the system's performance and analyze the correlation between the calculated sedentariness index and clinical assessments, with the goal of validating its effectiveness as a tool for promoting healthy aging.

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