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Sensor-Based Real-Time Monitoring Approach for Multi-Participant Workout Intensity Management

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Abstract: One of the significant advantages of technological evolution is the greater ease of collecting and analyzing data. Miniaturization, wireless communication protocols and IoT allow the use of sensors to collect data, with all the potential to support decision making in real time. In this paper, we describe the design and implementation of a digital solution to guide the intensity of training or physical activity, based on heart rate wearable sensors applied to participants in group sessions. Our system, featuring a unified engine that simplifies sensor management and minimizes user disruption, has been proven effective for real-time monitoring. It includes custom alerts during variable-intensity workouts, and ensures data preservation for subsequent analysis by physiologists or clinicians. This solution has been used in sessions of up to six participants and sensors up to 12 m away from the gateway device. We describe some challenges and constraints we face in collecting data from multiple and possibly different sensors simultaneously via Bluetooth Low Energy, and the approaches we follow to overcome them. We conduct an in-depth questionnaire to identify potential obstacles and drivers for system acceptance. We also discuss some possibilities for extension and improvement of our system.

Keywords: e-health; exercise; sensor; BLE; IoT

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1. Introduction

Digital solutions, the Internet of Things (IoT) [1], and Cyber–Physical Systems [2] have been accompanying our way of life in an increasingly continuous and omnipresent way. We have access to various decision support tools and software with intelligent features which are based on data. Sensors (and actuators) form an interface between the physical world and the digital realm. Through sensors, computerized systems receive data on various parameters related to a person or a natural element, either for immediate verification or for storage and later analysis. According to the World Health Organization, digital health should be an integral part of health priorities [3]. Its strategy to promote health and well-being emphasizes the importance of accelerating the development and adoption of person-centered digital health solutions and developing infrastructure to use health data. Chen et al. [4] proposed smart clothing as an innovative health monitoring system. Using a new textile manufacturing technique, they tried to mitigate the shortcomings of traditional wearable devices, such as discomfort during long-term wear and complex operation. The authors also outlined several applications driven by this smart clothing technology and big data clouds. Deng et al. [5] reviewed some achievements and recent progress of wearable systems, from their materials and manufacturing process to how they are extensively used to monitor basic human physiological signals, such as oxygen saturation, blood pressure, and heart rate (HR). In another publication on digital health, the authors asserted that wearable sensors enable remote patient monitoring, helping to reduce hospital visits, increasing convenience and reducing costs. The authors also stated that sensors play an important role in personalized and accessible healthcare [6].

The primary goal of our work is to develop a monitoring solution for the real-time analysis of training intensity through sensor data that applies to a group of people undergoing physical activity, within the context of rehabilitation therapies or for healthy individuals engaged in sports activities, particularly in nearby settings like within a gym room. Although there is a diverse and growing supply of wearable sensors for monitoring activity and health indicators, we find that the most accurate and least intrusive ones have a higher price. In general, each of these sensors requires the setup of a connecting software or device. When working with groups of people in the same space, one of the challenges we aim to overcome is finding a solution that does not require a dedicated interconnection device for each individual sensor or person.

Interoperability is crucial for reusing existing equipment, whether from the participants or belonging to the institution hosting the physical activity. Therefore, another challenge we set for ourselves was achieving multi-brand compatibility, avoiding the need to acquire all sensors from the same model.

Section 2 provides an overview of some relevant existing studies and systems. We present our approach in Section 3, detailing each component of the designed solution and how users interact with the system. Section 4 covers the experiments conducted to validate the system. Based on the findings and obtained results, Section 5 offers a discussion. Finally, Section 6 provides general considerations about this work and outlines potential directions for future improvements or extensions to the system.

2. Related Work

The scientific literature includes various works on the construction and use of HR sensors. In [7], the authors demonstrated the feasibility of HR prediction using a smart pen. In this study, data collection involved an experiment with eight volunteers who wrote the alphabet continuously for five minutes. The authors compared the HR data extracted from STABILO's DigiPen's accelerometer to standard ECG monitor readouts, for evaluation. To reduce interference during data collection, both the smart pen and the ECG instruments were connected to separate independent devices. The pen data allowed for accurate HR determination for all participants, with a deviation of 0.76 bpm.

In 2015, Kakria et al. developed a real-time heart monitoring system featuring a two-way communication interface between the doctor and remote patients using a smartphone and wearable sensors [8]. Smartphones served as hubs for gathering data from various sensors that measured heart rate, blood pressure, and body temperature. The information was then transmitted by these handheld devices to a web server via GPRS/3G or Wi-Fi, enabling physicians to diagnose patients' conditions. The proposed system could monitor multiple patients simultaneously. This approach was evaluated with 40 individuals using Android devices, under the supervision of experts. The authors found that one physician could monitor 15 to 25 remote patients if fully dedicated to this task, depending on the complexity of the patients' conditions.

In sports, wearable technology is important to improve performance through real-time data analysis and tracking for both amateur and professional practitioners [9,10]. The usefulness of HR monitoring in physical exercise was described in [11]. The authors claimed that it is essential for physicians (and other professionals) to use HR as an indicator of physical effort. Manual HR measurement may yield inaccurate/miscalculated results, or even require interrupting the exercise to take the measurement. Using devices to simultaneously read multiple variables, both internal (heart rate, respiratory rate) as well as external (accelerometry, speed, temperature, etc.), has enabled effective physical activity monitoring. Such devices help to increase the confidence of those who engage in exercise.

Measuring the HR of multiple individuals in close range is not very common. An overview of the main strategies that have been proposed for non-invasive HR monitoring in extramural and home settings was presented in [12]. Many of these approaches are sensitive to signal interference, as well as the body positions and distances between individuals when monitoring multiple people, or the distance between the subject and the (microphone or camera) signal receiver.

A recent study by Tran et al. [13] announced a non-invasive HR monitoring solution for multiple individuals using a commodity speaker and microphone array. The authors successfully measured the HR of two people sitting side by side, with an error of 0.6 bpm. They claimed that the system can effectively monitor up to four people in close proximity. Additionally, they noted a potential limitation related to acoustic-based methods: the approach can be affected by body movement and motion noise.

In terms of commercial solutions with potential application for multiple sensors, we identified SquadHR [14] in the Apple App Store (https://apps.apple.com/pt/app/squad-hr/id6468002688, accessed on 19 July 2024). This application was developed by Trackteam, a company specializing in creating coaching tools that leverage data insights from smartphones and sensors. SquadHR can be run on an iPhone or an iPad. In the personal use version, which is the only free option, this application allows tracking a single heart rate sensor, recording sessions and viewing and sharing workout summaries. A training score is calculated as the product of the training minutes for five heart rate zones multiplied by a coefficient relative to each zone. It supports all Bluetooth HR sensors compatible with iPhone, but it is not compatible with Android devices. For displaying real-time HR from multiple sensors on one iPhone, the "Group Training" license type is required, which involves a monthly payment, or annual payment alternative. The maximum number of simultaneously connected sensors depends on the iOS device's Bluetooth capabilities, ranging from 7 on a 9th generation iPad to up to 14 on the latest model iPhone or iPad with Bluetooth 5. SquadLink is a complementary application that runs on various iPhone devices and which SquadHR can connect with, to extend the data sources up to a maximum of 45 participants. In addition to requiring a uniform set of devices, it also needs a paid "Team subscription" license, primarily designed for gyms or sports clubs.

Pulse Monitor (https://www.pulsemonitor.net/, accessed on 23 July 2024) is another commercially oriented service designed to monitor the heart rates of participants in fitness clubs and indoor cycling studios. Its core module is a monitoring application that runs on a computer with a Windows operating system and an ANT+ receiver, allowing the monitoring of up to 42 participants. The system requires participants to wear a chest heart rate monitor with ANT+, a wireless technology designed for low-power, bidirectional communication between devices. Pulse Monitor displays exercise intensity using a color-coded system organized into five cardio zones, each representing a range of the percentage of maximum HR. The system can operate in two modes: training session and open workout mode. The former mode includes a setup for selecting participants, assigning sensor belts, and setting the maximum HR. The open workout mode does not require a supervising trainer but does not display participants' names or personalized indicators, assuming a maximum HR of 180 bpm [15]. This solution is available in several plans, and currently, a subscription to one of the three paid plans is required for monitoring more than two simultaneous participants.

3. Materials and Methods

3.1. Foundation and Purpose

This work addresses a specific need to support physiologists (or other professionals) during training sessions involving multiple participants simultaneously using equipment like exercise bikes or running treadmills. The solution is also applicable to other types of equipment and exercises. Our approach combines real-time analysis, with programmable alarms, and instantaneous and aggregated visualization of the effort level for the whole group of session participants.

While collecting HR data, the system monitors the training intensity for each participant and displays to the user a quantitative effort indicator, which can be in one of the following forms:

1. The absolute HR value, and how it varies throughout the session;
2. Whether the HR remains within a target range, between the lower and upper thresholds;
3. The participant's HR zone, and its correspondence or not with the target training zone at that moment for sessions with multiple intensity levels.

The first two indicator forms are designed to monitor training intensity for each participant individually, without inter-participant analysis. People with different levels of physical fitness might exhibit the same HR value at times, but this may correspond to distinct effort levels for each of them. The third indicator is recommended to compare the effort between the participants, and is essential for sessions involving groups with heterogeneous physical conditions. HR zones, from 1 to 10, are determined by the system as ten consecutive intervals along the useful HR range, between the resting HR and the maximum HR, inspired by the Karvonen formula [16]. Both resting and maximum HR values are specific to each participant and must be entered into the system. For a healthy participant, the maximum HR can be determined through specific exercise stress testing. Alternatively, in less rigorous contexts, a general formula can also be used, where the maximum HR is estimated as 220 minus the participant's age.

3.2. System Operation and Interface

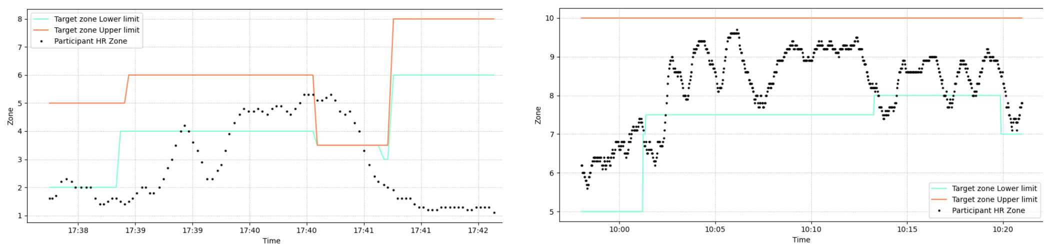
While the software is running, the system can be accessed through a web interface using a notebook computer or tablet browser. Starting by describing the system user's perspective, after logging in, users will have the options corresponding to their profile, which can be administrator or session coordinator. It is important to clarify the difference between a system user and a training session participant. Only the first has an account to perform actions in the system, or to perform analyses or consult records. The second concept corresponds to each person participating in the training session, and who, with consent, is being monitored by the system through data collected from wearable sensors.

Less frequently used, the administration profile is dedicated to maintenance operations and also for user profile management, which involves creating or removing user accounts or resetting a user's password. However, each user can also autonomously change the password. The most common access is performed with the session coordinator profile, which is a type of user responsible for managing the creation and monitoring of a training session.

After logging in, the home page shows a list of sessions held and a list of participants as illustrated in Figure 1. For each known participant in a training session, a record is kept with minimal personal data, but enough to distinguish them by name from other participants during monitoring. The participant's threshold HR values are stored in this record to support monitoring and the calculation of personalized effort zones.

Figure 1. Home view for coordinators: history of sessions held and participant records lists.

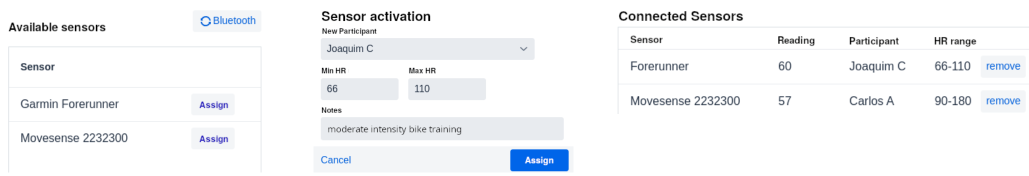
By opening the session details in the first grid, it is possible to consult an information summary, including the session's start and end times, the participants, and their sensors. Additionally, graphs displaying the participant's HR and HR zones can be viewed. Figure 2 illustrates the second option, with a graphical representation of the HR zones over time (in dots) and the desired target zone (if a single line) or the zone thresholds (if two lines, as at the beginning of Figure 2a, where the goal is an HR zone between 2 and 5). We can see that at 17:40, the first participant was within the target zone, but remained almost the entire time below the minimum intended intensity. On the other hand, Figure 2b indicates a good correspondence between the effort level of the second participant and the intended intensity over time.



(**a**) Poor performance. (**b**) Good performance.

Figure 2. Visual data representations: two participant HR zones. In (**a**), there is little alignment with the training goal, whereas in (**b**) the participant stayed predominantly within the target zone.

To create a new session, the coordinator defines the session name. Some fields, such as the session coordinator and the date, are automatically filled in. Afterward, it is necessary to assign sensors to participants as illustrated in Figure 3. On the left (Figure 3a), we can see how the system lists the names of the available HR sensors, meaning that they have been automatically detected and have not yet been assigned to anyone. Each sensor is associated to one participant who has not yet been selected as shown in the middle image (Figure 3b). The resting and maximum HR values for that participant are pre-filled with default values from the participant's record but can be adjusted at this point and for this session's scope. Once all participants are registered, a confirmation grid displays all sensor/participant pairs, including a preview of each sensor's data as shown in the second column of Figure 3c.



(**a**) Sensor detection. (**b**) Sensor assignment. (**c**) List of connected sensors.

Figure 3. Session setup: sequence of steps to assign a sensor to a participant. (**a**) Listing two active sensors not yet assigned. (**b**) Pairing a sensor with a participant (named Joaquim) and his lower and upper HR limits. (**c**) Confirmation grid with the already activated sensor/participant pairs.

The coordinator can now start the session, at which point the system enters the exercise monitoring mode and begins collecting and storing data from the sensors. At this stage, the system displays a monitoring dashboard, showing real-time HR data from each participant, along with a bar graph representing the HR trends over the last 30 s as depicted in Figure 4. This allows the coordinator to have an accurate and easy readable perception of the training intensity for each person in the group. When certain customized and rule-defined circumstances occur, alerts are shown to immediately notify the coordinator, or the group if they are watching the panel. Alerts are visual, with changes that stand out from the regular panel, and can optionally include audible beeps. The typical alert criteria are if the observed level of effort is too high, or when it diverges from the target training intensity. At the top right of Figure 4, we see an example of an alert indicating intensity above the limit for participant Carlos.

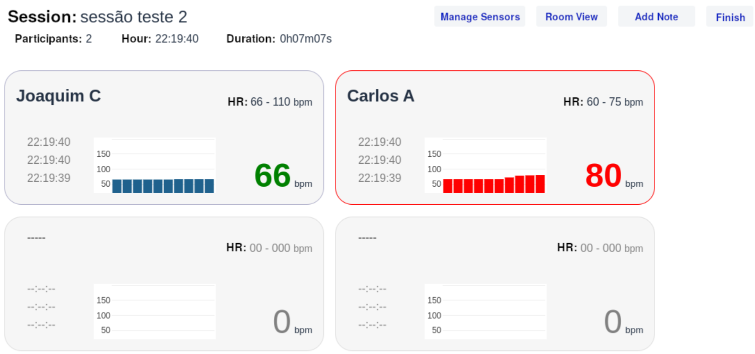


Figure 4. Session monitoring dashboard with two participants.

In this same example, the time displayed below the participant's name shows the most recent timestamp of data received from his sensor, helping to confirm the recency and the communications status.

For interval training, or sessions with variable intensity, the coordinator has a panel to adjust the desired intensity levels over time as shown in Figure 5. The buttons on the right ("Target Zone") are used to increase or decrease the limits for the ideal HR zone in a given phase of the activity.

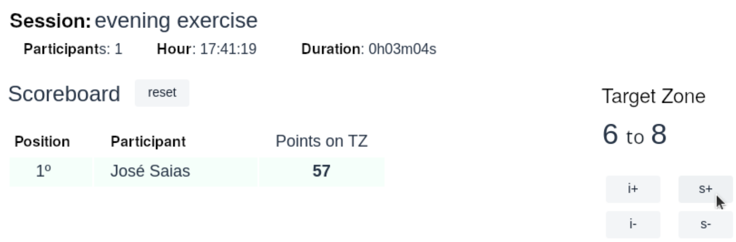
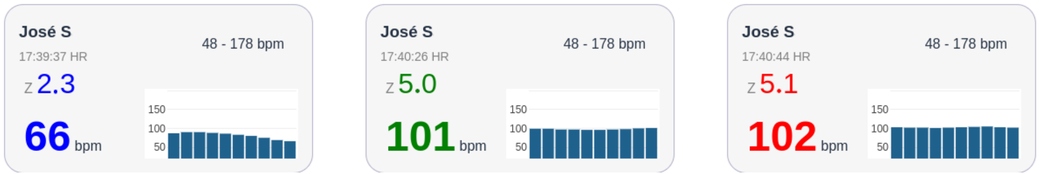


Figure 5. Variable intensity mode: effort zone control widget.

In this operation mode, the monitoring dashboard will also display an indicator for the participant's HR zone, calculated based on their specific parameters. This zone indicator allows us to compare the effort level between participants. Figure 6 shows the monitoring panel including the HR zone (to the left, above the HR) across three scenarios: (a) the participant's effort is below the target intensity; (b) the participant's zone is within the intended range; (c) the HR zone exceeds the intended range.



(**a**) Blue notice: below target. (**b**) Green: proper zone level. (**c**) Red notice: beyond target.

Figure 6. Monitoring panel in variable intensity mode: zone indicator and color codes. (**a**) Zone indicator below the training objective. (**b**) Participant zone indicator complies with the intended effort level. (**c**) The HR zone value is very high considering the session objective.

On the right, the HR zone level 5.1 means that the HR value (102) is in the fifth decile of the range $[48, 178]$, with 48 and 178 being the resting and maximum HR values for that participant.

Throughout the session, notes can be entered regarding general occurrences, user-specific remarks, or any complications. These textual records will help later in the subsequent analysis conducted by the session coordinator or other experts.

At the end of the physical activity, the session is marked as closed. The system records the end time and stops storing the data streams coming from the sensors. After that, participants may remove the sensors. The coordinator will see a session summary page that includes the session duration, the coordinator's name, the participants involved, and which sensors were used as illustrated in Figure 7.

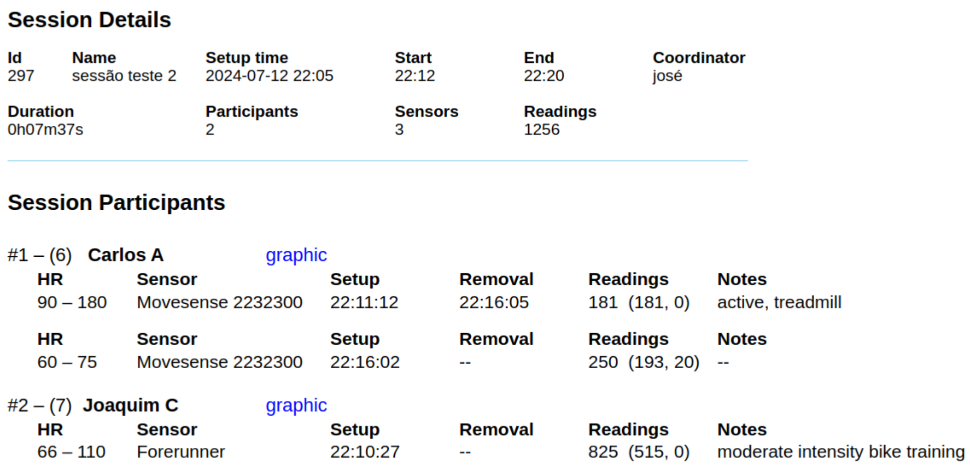


Figure 7. Session summary: time, duration, participants, sensors, and indicators.

Coordinator users with an active account can consult previously created session records to analyze a participant's history and to eventually adjust the training plan for the next session.

In the participant details view (accessible from the participants list on the home page), we can see which sessions the participant has attended and access graphs showing their corresponding HR data. Optionally, if there is an additional large monitor available for visual monitoring for the entire group, the system offers a "Room View" option, which opens a new browser window that can be placed on this second monitor. The same dashboard is shown but without the operational control buttons. This setup also allows the session coordinator to write notes in a separate control window, ensuring greater privacy. To further increase visibility during session monitoring, it is also possible to enlarge the interface using the browser's zoom controls.

During a training session, it is typical for each participant to wear a single sensor. However, it may be necessary to replace the sensor midway through, which is not expected but accounted for in case of unforeseen events, such as battery drain. In this case, there may be two sensor registrations for the participant, with the first one having a recorded removal time. The HR data for this participant will be fully available, being optionally separable for each sensor in two time series.

In the event that a sensor exchange operation occurs for a participant, the data collection (and monitoring in room view) for the remaining participants will continue without interruption. This sensor reassignment operation can be completed in approximately 15 s by the coordinator (including the physical placement of wearables).

If a participant moves too far away, the sensor data transmission will stop. Additionally, if the sensor band falls off and the contacts are no longer properly positioned, the sensor may also cease transmitting data. In both cases, either the participant's return to a distance within the communication range, or adjusting the sensor placement, respectively, will be sufficient to automatically resume data collection and monitoring from that sensor.

In these special situations, to minimize gaps in sensor data, the system will display a red alert for any sensor/participant whose last data transmission exceeds a configurable maximum period (e.g., 10 s). This allows the session coordinator to intervene if necessary, ensuring that no participant remains unmonitored without detection.

If communication does not resume automatically, the coordinator can use a system option to refresh the sensor association. This operation will attempt (a) device re-bonding and (b) resetting the Bluetooth controller. The first action does not impact the other active sensors. The second action, if applied, could inhibit data collection from other sensors for 5 to 10 s. If this action does not solve the issue, the coordinator can assign a new sensor to that participant using the "Manage Sensors" operation during the session, and without interrupting data collection from the other sensors.

3.3. Infrastructure and Technology

The sessions' exercise can take place in a gym room, on a sports court, or, in a healthcare context, at a physical rehabilitation facility. Since participants are spread across the space and can even move to a corridor, or switch between equipment, for instance, between a treadmill and an exercise bike, we designed an IoT-based data collection solution. Figure 8 shows the general architecture of the developed system, from sensors to visualization components. A sensor gateway module (GW) is deployed to collect data from nearby sources and stream them upwards to the control module, the system's central node responsible for processing, analysis and storage management. In terms of platform, for the gateway component, to which the sensors are paired, we use a mini-PC equipped with a Bluetooth controller version 5.3, and a network interface (wired or wireless) to upstream data to the control module. Currently, both the gateway and control modules run the Ubuntu Linux operating system and use Java (JRE 17+) to execute the system software. We use BlueZ (https://www.bluez.org/about, accessed on 6 June 2024) to interact with the Bluetooth controller on Linux, and the blessed-bluez (https://github.com/weliem/blessed-bluez, accessed on 6 June 2024) library for operations and communication with the sensors.

The control module is a Java application whose web component was developed with Vaadin (https://vaadin.com, accessed on 6 June 2024), an open-source framework for the development of interactive and responsive web applications.

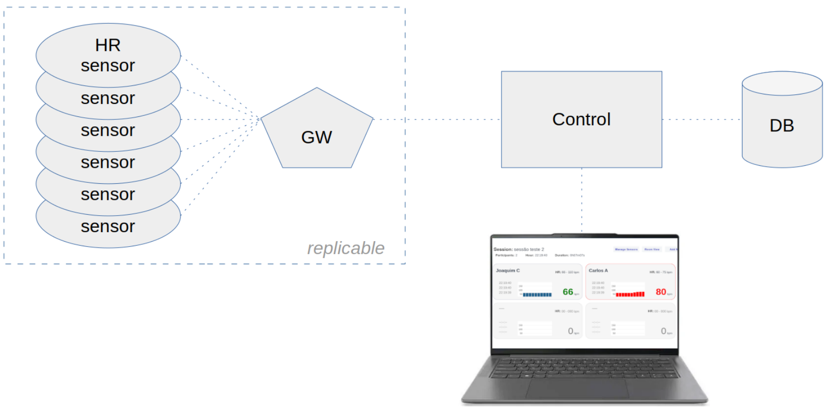


Figure 8. Monitoring system architecture: modules and interconnections between them.

The received data are used for visualization and passed to the storage module (DB), which relies on a Postgres database for persistence. Alternative databases can also be used, provided they support high-speed data ingestion and complex data analysis capabilities.

From the beginning of this project, HR was chosen as the primary parameter to be measured using sensors. Due to power constraints, the communication between such sensors and the gateway node is based on a short-range and low-power wireless protocol: Bluetooth Low Energy (BLE) [17]. Other options, such as ANT+ and Zigbee, were also considered. Compared to BLE, ANT+ has a slight disadvantage in battery power consumption, and apart from the fitness area, there is less equipment that supports it, which could limit future vendor options if we want to associate complementary sensors. Zigbee is more appropriate for communications over distances slightly greater than those of interest in this work. It may be relevant for future extensions to this system, for communication with more distant actuator devices, where messages are not as frequent. The BLE protocol proved to be a good balance between the data transmission rate, power consumption, and broad hardware compatibility, making it the chosen option. The gateway software implementation prioritized communication with this type of sensor, including those from Movesense (https://www.movesense.com, accessed on 4 June 2024), which our partners already had. But to meet our interoperability goal, we used a brand-independent communication form.

The maximum number of sensors we can connect to a single Bluetooth controller depends on several factors, including the gateway device software and the Bluetooth version. Under typical conditions, a Bluetooth controller version 5.x might handle 7 to 10 BLE active devices. Whenever the number of participants is greater than the maximum supported by a single Bluetooth controller, we can activate another gateway component. Therefore, the box on the left side (representing the Gateway and a small number of sensors) of Figure 8 can be multiplied, depending on the number of participants.

The communication between the sensor gateway node(s) and the central control module is based on standard networking using REST over HTTP. As an alternative, MQTT can also be used. Depending on the number of sensors and the data volume, and also on the frequency requirement for data recency in monitoring, the sensor gateway can be adjusted to send batch transmissions of multiple readings for greater efficiency.

In a monitoring system, it is crucial to avoid losing communication with a sensor. At least the system must be capable of detecting such a loss if it occurs during a training session. It is known that in these wireless communication protocols with sensors, the signal can be impacted by various factors, including the sensor's battery level, the distance between the antennas, obstacles or physical barriers in the signal path, and possible interference from other wireless signals.

3.4. Validation Methods

For interoperability assessment, concerning wearable sensors and to verify brand-independent capability, we tested the collection of HR data from distinct devices. In addition to the Movesense sensors, which were available to us in greater number, the system successfully worked with Polar H10 (https://www.polar.com/pt/sensors/h10, accessed on 4 June 2024) equipment and with sports smartwatches capable of HR transmission during exercise, such as the Garmin Forerunner 255 (https://www.garmin.com/en-IE/p/780139#specs, accessed on 4 June 2024) and others. We began with association tests to validate sensor detection and effective data communication. Next, we measured the communication range. For each sensor type, we progressively increased the distance from the gateway until the data transmission was interrupted. Multiple repetitions were conducted in both a typical indoor environment (a room with people and various devices) and an open outdoor environment without barriers or interference. From each series of repetitions with the same setup, we recorded the average distance value. The stored records, the session notes, and the system logs were subsequently analyzed for complementary information regarding special cases, such as eventual transmission losses.

To understand how users perceive the system we followed a Technology Acceptance Model (TAM)-based approach, a widely used model in information systems and technology adoption research [18]. An extended TAM-type questionnaire was prepared, having mostly Likert scale-type closed-ended questions. It includes the two TAM base aspects, perceived usefulness and perceived ease of use, as well as additional aspects such as peer influence, facilitating conditions, user satisfaction, and usage intention. Please refer to Appendix A for the full questionnaire.

We asked session coordinators, who use this system in partner entities, to respond. To diversify the survey and obtain a reasonable number of responses, we broadened the distribution of the questionnaire to other users, who, until then, were unaware of the existence of this system. The inclusion criterion for this study was having prior experience in using sensors and interpreting physical activity indicators, as well as the ability to monitor activities involving multiple participants. Each questionnaire response was based on two or more training sessions using the system. The first session served to explain the system's operation, while the subsequent sessions were controlled by the responding user. In each experiment, in addition to the user, one or two researchers from this project were present to demonstrate the procedures and ensure protocol compliance. Additionally, two to six other people were required to wear sensors for 20 min or more during exercises of varying intensity.

TAM questionnaires can reveal specific issues or concerns that may hinder users from adopting a technology, such as perceived complexity or lack of perceived benefits. Moreover, that is what we intend to analyze from the data: to identify possible barriers or favorable factors in the users' perception of the system. We did not aim to assess the impact of the exercise on session participants, nor to differentiate between questionnaire respondents.

We employed common TAM data analysis procedures, including descriptive statistics and reliability analysis. The purpose of descriptive statistics is to understand the data main features, such as central tendency and data dispersion. The reliability of the scale-type questionnaire items was evaluated using Cronbach's Alpha [19], a measure of internal consistency.

The questionnaire was filled out via browser, using Google Forms. The data were exported to an XLSX spreadsheet format. Statistical analysis was conducted using Python, the Pandas library (https://pandas.pydata.org/, accessed on 19 June 2024), and the Pingouin open-source statistical package (https://pingouin-stats.org/, accessed on 19 June 2024) (the files are available in Supplementary Material). After reviewing the initial results, a *t*-test and a Mann–Whitney U test [20] were applied in an additional experiment to determine if there were relevant differences in the perceived usefulness between two user types.

4. Results

4.1. Analyzing the Interaction with Sensors

The results of our experiments concerning the interaction between our system and the sensors are as follows. In terms of spatial constraints, we noticed that the maximum distance between the gateway component and the sensors worn by the participants was sufficient for session monitoring. The gateway successfully received data from multiple sensors up to 12 m away. Under favorable conditions, outdoors and without obstacles, the communication with the sensor remained effective over greater distances as shown in Table 1.

Table 1. Useful range observed in BLE communications between the system and the sensors.

Sensor Type	Range	Maximum Range/Ideal Setting
Movesense Active	12 m	15 m
Polar H10	12 m	16 m
Garmin Forerunner 255	12 m	25 m

For the tested smartwatch, in a favorable environment, the communication range more than doubled. However, it became highly sensitive to the direction or alignment between the watch and the gateway's Bluetooth controller. The scenario with the highest system load, observed on multiple occasions, involved approximately 1100 readings per minute being processed by the system over a 45 min period.

The loss of transmission was not always related to the communication range limit or to the sensor battery. In fact, about 90% of the cases of occasional interruption in data collection had to do with sensor placement, or displacement of their contact points due to body movements in training.

4.2. Analyzing User Perception

In addition to the difficulty of recruiting volunteers who met the coordinator participation criteria, there was also the challenge of reserving the exercise space within the necessary time frame and coordinating the schedules of everyone involved, which prevented us from gathering more than ten respondents.

The results of the questionnaire data analysis using descriptive statistics are presented in Table 2.

Table 2. Descriptive statistics of the ETAM questionnaire responses. Scale responses range from 1 (Strongly Disagree) to 5 (Strongly Agree).

Questionnaire Item	**Descriptive Statistics**			
Respondent	Data distribution			
age	1× 18–25; 4× 26–35; 4× 36–45; 1× 46–55 yo			
gender	3 Female, 7 Male			
activity sector	Health: 3; Sports: 4; Technology: 3			
frequency of system use	6: up to 5 times; 2: more than 5 times; 2: weekly			
Central tendency and variability of Likert scale answers				
Perceived Usefulness	mean	std	min	max
improves my performance	4.40	0.84	3.0	5.0
increases my productivity	4.40	0.70	3.0	5.0
enhances my effectiveness	4.70	0.67	3.0	5.0
Perceived Ease of Use	mean	std	min	max
I find this technology easy to use	4.90	0.32	4.0	5.0
learning to operate this technology is/was easy	4.90	0.32	4.0	5.0
this technology is user friendly	4.70	0.48	4.0	5.0
Social Influence	mean	std	min	max
people who influence my behavior think I should use	3.60	0.84	3.0	5.0
people whose opinions I value prefer that I use	3.40	0.97	2.0	5.0
my peers use this technology	2.30	1.49	1.0	5.0
Facilitating Conditions	mean	std	min	max
I have the resources required	4.10	0.74	3.0	5.0
I have the necessary knowledge to use	4.80	0.42	4.0	5.0
this technology is compatible with other systems I use	4.00	0.94	3.0	5.0
User Satisfaction	mean	std	min	max
I am satisfied with the functionality	4.80	0.42	4.0	5.0
this technology meets my expectations	4.50	0.71	3.0	5.0
overall, I am pleased with this technology	4.60	0.52	4.0	5.0
Behavioral Intention to Use	mean	std	min	max
I intend to use this technology regularly	3.60	0.97	3.0	5.0
I will recommend this technology to others	4.50	0.53	4.0	5.0
I plan to continue using this technology in the future	4.10	0.99	3.0	5.0

Concerning the initial three questions related to perceived usefulness, we have all scale answer values between three (Neutral) and five (Strongly Agree). The average response value for the "enhances my effectiveness" item is 4.7, with a standard deviation of 0.67. The answer average value equal to 4.9 in "easy to use" and "learning was easy" items indicates that users find this system easy to use. Despite this, the higher standard deviation in the next group's item suggests that it may in fact improve in terms of user friendliness. By examining the minimum and maximum columns, we observe that the range of response values is broader for the items related to social influence. In the third item of this group, responses range from 1 to 5, indicating that some respondents have colleagues who use this system, while others do not. For the three questionnaire items related to facilitating conditions, the average response values range between 4.0 and 4.8, with a standard deviation of less than 1. The responses trend between Agree and Strongly

Agree. User satisfaction items show a high average response. Within this block, satisfaction with functionality has the highest mean of 4.8, and the lowest standard deviation of 0.42. This suggests that satisfaction is more closely related to functionality than to the technology involved. Regarding the intention to use the system regularly, there is a tendency between Neutral and Agree, with an average scale value of 3.6. The lower values are not surprising, as some questionnaire respondents were sporadic users. All respondents answered Agree or Strongly Agree regarding recommending this solution to others. The response values for this item range from a minimum of 4 to a maximum of 5. In the last item, regarding the intention to continue using the technology in the future, responses range from 3 (Neutral) to 5 (Strongly Agree), with 4.1 being the average value.

The second stage in analyzing the TAM questionnaire results involves assessing reliability. A Cronbach's Alpha value above 0.7 is typically considered a threshold for acceptable reliability [19]. We applied this method to measure the internal consistency of the 18 scale-type questionnaire items, and the result was 0.897, which is substantially above the threshold. We concluded that the questionnaire data have a good reliability level.

In the opinions and suggestions conveyed by open-ended questions at the end of the questionnaire, it was mentioned that the system interface is friendly and intuitive to use.

One user also mentioned that the gamification aspect, with the introduction of a scoreboard (shown on the left side of Figure 5) related to time spent within the target training zone, serves as a positive stimulus for exercise participants.

Revisiting the perceived usefulness items' answers, ranging from Neutral as the minimum to Strongly Agree as the maximum as seen in Table 2, we decided to reanalyze the data for these three items according to the frequency of use variable. We sought to find out if there are noticeable differences in the perception of usefulness between frequent users and occasional users. In Table 3, we can see the mean value and standard deviation of data in these questionnaire items by frequency of use. Reading the table from left to right, it is clear that the average agreement in the three items increases with the frequency of use.

The table presents average values. It still remains to consider the weight of each column (each category of frequency of use) within the entire dataset.

Table 3. Perceived usefulness scales' data per frequency of use.

Questionnaire Item	Frequency of Use					
	Up to 5 Times		More than 5 Times		Regular Weekly	
	mean	std	mean	std	mean	std
improves my performance	4.17	0.98	4.50	0.71	5.0	0.0
increases my productivity	4.0	0.63	5.0	0.0	5.0	0.0
enhances my effectiveness	4.50	0.84	5.0	0.0	5.0	0.0

We divided the respondents into two groups based on their usage frequency:

- Occasional use—who responded that they had used the system up to 5 times;
- Frequent or intermediate use—who used the system weekly or had accumulated more than five uses.

The group sizes were six and four, respectively. To determine if there is a significant difference between the two groups, we applied a *t*-test. To handle unequal lengths, we truncated the longest set to match the length of the shortest one for *t*-test processing. Since the elimination of instances in a small set can lead to information loss, we chose to carry out a complementary analysis that considers all available records. A Mann–Whitney U test [20], a non-parametric statistical test used to compare two groups for non-normal data distribution cases, was applied using SciPy Stats (https://docs.scipy.org/doc/scipy/reference/stats.html, accessed on 19 June 2024). Considering the p-value results for both tests, displayed in Table 4, only for the "increases my productivity" item can we conclude that the difference between the groups is statistically significant (p-value < 0.05). For the other two questionnaire items, the p-value results do not allow us to make the same conclusion statistically, despite this being our intuition.

Table 4. Assessing difference per group on perceived usefulness items.

Questionnaire Item	*t*-Test *p*-Value	Mann–Whitney U Test *p*-Value
improves my performance	0.391	0.397
increases my productivity	0.015	0.025
enhances my effectiveness	0.215	0.287

5. Discussion

Given that this project was initially driven by a real need, we consider that one of its key outcomes is the achievement of an effective solution to address that need, a system for monitoring the simultaneous physical exercise of a group of participants based on HR sensors. The experiments conducted with three types of sensors from different manufacturers demonstrate that the choice of BLE for edge communication was appropriate, fostering compatibility, and thereby broadening the range of HR monitors or other sensors we might use in the future. Based on the communication range experiments and the results presented in Table 1, it turned out that 12 m is the safe distance we obtained for simultaneous communications with the various sensors. With this diagnosis, we note that a single gateway is sufficient for scenarios where the area to be covered does not exceed 24 m in diameter, which is suitable for common exercise rooms. Other setups are still possible for larger spaces, as previously mentioned, by activating another GW component coordinated by the same control node and the sensors being split per GW.

All cases of transmission interruption between a sensor and the system are detectable in the data recency check, which issues a warning when necessary. The participant is then instructed to readjust the sensor. A few seconds later, the sensor readings reappear on the dashboard.

From the analysis of the technology acceptance questionnaire answers, summarized in Table 2, we see that respondents have a favorable perception of this system usefulness, with a strong agreement with its performance/productivity/effectiveness benefits. On user satisfaction, there was a greater focus on the system's functionality rather than on the technology itself or on how it meets expectations. In the questionnaire items relating to behavioral intention to use, we emphasize the high level of agreement with "will recommend this technology to others". The intention to use the system regularly is a little lower, at 3.6, which seems acceptable to us as there are occasional users. The high value in the Cronbach's alpha result indicates that the scale-type items in this questionnaire have good reliability. From Table 3, we infer that the most frequent users are the ones who value the system's advantages the most. The statistical tests to compare between the "occasional use" and "frequent or intermediate use" groups' perceived usefulness have a high p-value on the perceived improvements in performance and effectiveness. For the perception of productivity gains, both tests suggest that the difference between the two groups of users is statistically significant. The lack of a statistically significant difference for two of these items may be due to the small sample size. As mentioned earlier, each questionnaire response involves a complexity that made it difficult to increase the number of valid respondents. Additionally, distinguishing between groups was not a primary objective of this study.

To the best of our knowledge, we found no non-commercial software providing the exact same functionality: a unified monitoring dashboard with real-time analysis and control of HR and HR zones for multi-participant sessions having a single coordinator. Typical solutions involving a separate control application for each sensor would not be compatible with the integrated monitoring of groups of people in the same exercise room.

We now present a brief comparison with the systems mentioned in Section 2. A smartphone is required for each patient monitored by the system in [8], which we view as a disadvantage, as it entails prerequisites and additional complexity for session setup.

Furthermore, that system is designed for remote monitoring and not for participants in the same physical space. The acoustic-based method in [13] can measure HR for two people sitting side by side, but it is vulnerable to body movement and motion noise, which would make it unfeasible for an exercise room where there is conversation and rotation between stations/equipment.

The two commercial solutions, SquadHR and Pulse Monitor, although more comparable to our project, fall short in their ability to monitor groups of six or more without paid subscriptions. SquadHR supports BLE HR sensors compatible with iPhone, and easy sensor management. Its training score is based on zones relative to maximum HR. We found no information regarding custom alarm features or variable criteria for interval training monitoring for use in color codes on the dashboard.

The Pulse Monitor system works with ANT+ compatible sensors. This has the advantage of facilitating the instant association of more than 7 sensors. But on the other hand, BLE is a more generic protocol, compatible with a wider range of devices. ANT+ is energy efficient but has a slight disadvantage in battery power consumption during data transmission, and its data transmission rates are typically slower than BLE. Battery preservation is important in our case, as our system is mostly used in sessions in which the same sensors are applied to different groups of people (although the participant's particular sensors may be used). The repeated use of sensors requires longer cycles of use between recharging or battery replacement, and therefore, energy consumption is relevant. Pulse Monitor has a user-friendly interface and shows an exercise intensity indicator based on maximum HR. Just as for the previous system, this intensity indicator is different from the one used in our system, as we considered not only the maximum HR but also the resting HR. More relevant than the difference in the number of zones or intervals, considering this lower threshold of the useful heart rate range is crucial for our work for monitoring that is robustly adapted to the participant.

6. Conclusions

We described the purpose, operation, and preliminary validation of a system designed for sensor-based workout guidance for in-person multi-participant sessions. When working with a set of small pieces of equipment that may vary significantly in hardware and/or protocols, the complexity of configuring them can sometimes be an obstacle to extracting value from their operation. We believe that this work helps to mitigate the complexity of working with sensors, particularly in scenarios involving groups of people in close proximity. It simplifies the sensor pairing process by providing a single unified system for all wearable devices, regardless of brand, along with an effective monitoring dashboard. Thus, we successfully addressed the two challenges outlined in Section 1 by combining the selection of independent protocols with the development of a new software module for our gateway, designed to support multiple connections and universal compatibility.

We identified some distinctions in comparison to similar recent systems mentioned in Section 2. The first relates to the calculation of the primary exercise intensity indicator, which we believe is more rigorous in our system. By incorporating a stricter zone calculation based on two HR thresholds, rather than the conventional maximum HR-based indicator, our system offers greater potential for application in healthcare. Equally relevant to the field of sports is the ability to dynamically manage the training target zone during the session, as well as the option to export not only HR data but also information on whether the training plan was followed. Additionally, our system provides dynamic, in-session color-coded warnings for training with varying intensity, to gauge the alignment between the current and planned intensities, rather than relying solely on static colors per HR zone.

The experiments carried out to analyze the technical aspects of the solution, along with the feedback from system users, referred to in Section 4, lead us to conclude that the project goals were successfully achieved. Although the number of questionnaire respondents was limited due to the need for users to coordinate training sessions with real monitored participants, the data analysis (Appendix A) points to a strong acceptance of our system, and recognition of its benefits. Statistical analysis also revealed that the most frequent users are the ones who most strongly agree that the system increases the coordinator's productivity.

As future work, we have several development paths planned. Beginning with communication with edge devices, we plan to support additional communication protocols to enhance compatibility and convenience. Another idea is to develop an additional software component for a remote gateway, which allows connecting to the control module. The intention is to jointly monitor a participant from his home alongside the on-premises participants group. Another experiment that we have not yet conducted, but which could be very useful in practice, is adjusting the Movesense sensor settings to reduce the frequency of HR readings transmission by half, with the aim of extending the device's battery life.

From an exercise physiologist's perspective, we could expand the monitoring to include additional parameters, as a complement to HR. In the realm of cyber–physical systems, just as we currently have rule-based alerts, we could also issue action orders to actuators on exercise equipment. This would enable the system to automatically adjust the exercise difficulty level, thereby completing the control loop. Lastly, we plan to explore effective methods for extending the area within range to increase the participants' freedom of movement. Although there are low-level adjustment techniques related to radio frequency [21], we sought to test a method at a higher abstraction level and whose gateway pairing approach is inspired by GSM hard handover.

Supplementary Materials: The questionnaire data and several statistical analysis files can be downloaded at: https://magno.di.uevora.pt/jsaias/electronics-2651549/supplementaryMaterial.zip (accessed on 12 September 2024).

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Extended Technology Acceptance Survey

Survey on users' perception of the UE HeartFit monitoring solution. The form must be answered by users with a coordinator/coach/therapist role.

User Characterization

Age: 18 to 25 yo; 26 to 35 yo; 36 to 45 yo; 46 to 55 yo; 56 to 65 yo; 66 years or older

Gender: Feminine; Masculine

Professional Activity Sector (scope of the access to this technology)

Health; Sport; Technology; Education; Other

How often have you used this software?

Occasional use (up to 5 times); Occasional use (more than 5 times); Regular monthly; Regular weekly; Daily; Occasionally two or more times a month

Perceived Usefulness

Using this technology improves my performance.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

This technology increases my productivity.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

This technology enhances my effectiveness.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

Perceived Ease of Use

I find this technology easy to use.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

Learning to operate this technology is/was easy for me.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

This technology is user-friendly.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

Social Influence

People who influence my behavior think I should use this technology.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

People whose opinions I value prefer that I use this technology.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

My peers use this technology.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

Facilitating Conditions

I have the resources required to use this technology. (technical resources or other requirements identified by the user)

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

I have the knowledge necessary to use this technology.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

This technology is compatible with other systems I use.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

User Satisfaction

I am satisfied with the functionality of this technology.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

This technology meets my expectations.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

Overall, I am pleased with this technology.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

Behavioral Intention to Use

I intend to use this technology regularly.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

I will recommend this technology to others.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

I plan to continue using this technology in the future.

1-Strongly Disagree | 2-Disagree | 3-Neutral | 4-Agree | 5-Strongly Agree

Open-Ended Questions

Which feature(s) do you appreciate most about this solution? (Optional)

[Open text box]

Do you have other comments or suggestions for improvements? (Optional)

[Open text box]

Conclusion

Thank you for completing the survey.

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