



Development and Evaluation of an IoT-Based System for Near-Real-Time Average Heart Rate Monitoring in Team Sports

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ABSTRACT

Continuous and objective real-time internal load monitoring is essential in team sports but practically challenging to implement simultaneously for multiple athletes. This study aimed to develop and evaluate Mohan Pulsehub, an Internet of Things (IoT)-based real-time physiological monitoring system for multi-athlete average heart rate (HR) tracking. Employing a Research and Development (R&D) design, the system integrated Polar H10 sensors, wireless communication networks, and a centralized dashboard. Testing involved fourteen provincial-level male kabaddi athletes during a 2 x 20-minute match simulation scenario. Data aggregation was managed simultaneously by a central Bluetooth Low Energy (BLE) gateway receiver. System validation assessed data transmission performance through latency and packet loss. Concurrent validity against a commercial benchmark utilized the Intraclass Correlation Coefficient (ICC) and Mean Absolute Error (MAE), while practical usability employed the System Usability Scale (SUS). Results indicated that the system successfully connected all fourteen sensors with a 99.72% transmission success rate, demonstrating an average latency of 186.4 ms and 0.28% packet loss. Data agreement was near-perfect (ICC = 0.998, MAE = 0.45 bpm). Furthermore, a preliminary usability evaluation by three end-users (a head coach, an assistant coach, and a performance analyst) yielded a mean SUS score of 84.3 ± 5.6 (individual scores: 78.8, 84.7, and 89.4, calculated using standard SUS item weighting). Conclusively, while independent physiological validity remains to be established, the study demonstrates that the developed IoT architecture provides robust data transmission integrity and near-perfect software agreement for Polar H10 data, serving as a reliable and user-friendly tool, supporting the feasibility of simultaneous near-real-time internal load monitoring in team sports.

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INTRODUCTION

Training load management is a crucial component in team sports due to the intermittent nature of training and match demands, which involve a combination of low to high intensity activities, sprints, and changes of direction. Suboptimal training load management can lead to an imbalance between the training stimulus and recovery, thereby potentially impairing performance and increasing the risk of fatigue and injury. Consequently, the objective and continuous monitoring of training loads is increasingly necessary for the coaching decision-making process (de Beukelaar & Mantini, 2023; Migliaccio et al., 2024; Włoch et al., 2025). Specifically, athlete physiological responses to training loads are assessed using internal load indicators, namely biometric metrics such as heart rate (HR) and heart rate variability (HRV) (Schumann et al., 2025; Seshadri et al., 2023). In team sports characterized by high-intensity physical contact and intermittent anaerobic movement phases, such as kabaddi, monitoring this internal load is highly essential yet challenging to be conducted precisely in the field.

Advancements in wearable technology have enabled more continuous measurement of internal load. Modern HR sensors are capable of accurately generating athlete physiological data during the training and matches. Recent literature indicates that such technologies are increasingly utilized for performance and recovery monitoring and are beginning to be directed toward a real-time data transmission (de Beukelaar & Mantini, 2023; Migliaccio et al., 2024; Su et al., 2025). In team sports, instantaneously available psychophysiological information is crucial for gaining insights into the athlete fatigue status (Teixeira et al., 2025). Nevertheless, the reliability of data transmission from wearable devices to coaches remains a significant issue, as the quality of monitoring systems heavily depends on wireless transmission stability and receiver device characteristics (Schumann et al., 2025; Włoch et al., 2025).

Furthermore, the availability of technology does not always align with the practical needs of coaches in the field. Leading commercial systems have provided athlete monitoring facilities. However, their application in developing countries frequently encounters barriers, such as the high cost of basic equipment and recurring software licenses. Moreover, many studies still focus on offline physiological post-training data analysis, whereas coaches require concise, easily interpretable, and real-time information to support substitution decisions or injury prevention during ongoing training sessions. A scoping review of coach perspectives highlighted that relevant and instantaneously accessible monitoring information is the most critical aspect in the implementation of sport systems (Timmerman et al., 2024).

These conditions reveal an urgent need for a monitoring system capable of acquiring internal load (HR) data using commercially available gold-standard sensors, transmitting it wirelessly without significant delay (latency) and presenting it in a user-friendly interface for coaches. An Internet of Things (IoT)-based approach offers an opportunity to address this gap through the design of a local wireless transmission architecture and independent visualization (Su et al., 2025). Research is needed to specifically design and test the reliability of this real-time transmission network, making it practical and capable of reducing dependence on commercial software platforms for data visualization and management.

Based on this gap, the present study develops an IoT-based real-time physiological monitoring system focused on internal load monitoring in team sports. While existing commercial multi-athlete monitoring systems, such as Polar Team Pro, offer robust tracking capabilities, they often depend on proprietary ecosystems, high initial hardware investments, and recurring software licensing fees which limit their accessibility in resource-constrained environments. Furthermore, previous sports-IoT studies frequently focus on single-athlete

applications or post-session data analytics rather than simultaneous data acquisition. Therefore, the novelty of this study lies in its incremental technical and functional contributions. Technically, it engineers a cost-effective local IoT network architecture optimized to sustain simultaneous Bluetooth Low Energy (BLE) transmissions from multiple athletes (tested up to 14 devices) with low latency and minimal packet loss, operating independently of heavy cloud constraints. Functionally, it provides an accessible and license-free interactive dashboard named Mohan Pulsehub, empowering coaches with near-real-time physiological data visualization to support immediate on field decision making.

Prior to addressing its main objectives, this study evaluated three primary hypotheses. First (H1), the developed Mohan Pulsehub system can simultaneously acquire and transmit HR data from 14 BLE-enabled Polar H10 sensors with low latency and minimal packet loss during a simulated team-sport match. Second (H2), HR data displayed by Mohan Pulsehub demonstrate high agreement with synchronized HR data from the commercial benchmark application. Third (H3), Mohan Pulsehub exhibits acceptable preliminary usability among intended coaching and performance-support users.

This study aimed to develop and evaluate an IoT-based real-time internal training load monitoring system for team sports. Specifically, this research aimed to develop a real-time heart rate (HR) data acquisition and transmission system using wearable sensors and IoT technology, develop a centralized dashboard for multi-athlete HR visualization, evaluate data transmission performance based on latency and packet loss, evaluate the agreement of HR data between the developed system and a benchmark platform, and evaluate system usability using the System Usability Scale (SUS).

METHODS

Research Design

This study employed a Research and Development (R&D) design, adapting the comprehensive 10-step development model proposed by Borg & Gall (1989), into a simplified seven-stage framework. The product development also integrated an iterative prototyping approach (Pressman, 2015) to ensure that the resulting real-time physiological monitoring system functions optimally in team sport settings. This approach was selected because the study does not merely aim to examine relationships between variables, but rather focuses on product engineering, encompassing the integration of hardware, software, data communication systems, and a monitoring dashboard. The adaptation and simplification were justified by the specific scope of this research, which prioritized technical functional viability, expert consensus, and initial ecological field testing over mass production and broad commercial dissemination. The mapping of the original Borg & Gall stages to the adapted procedures conducted in this study is detailed in Table 1.

Table 1. Mapping of The Original Borg & Gall Framework to The Adapted R&D Stages

Original Borg & Gall (1989) Stages	Adapted Seven-Stage Framework	Description of Conducted Procedures
1. Research and information collecting	1. Needs analysis	Determining physiological parameters (HR) required for kabaddi training loads
2. Planning	2. System design	Designing the IoT architecture, dashboard interface, and hardware selection
3. Development of preliminary form of product	3. Initial prototype development	Assembling the Polar H10 sensors, communication modules, and Mohan Pulsehub dashboard

Original Borg & Gall (1989) Stages	Adapted Seven- Stage Framework	Description of Conducted Procedures
- (integrated into prototype phase)	4. System functional testing	Laboratory-based technical testing of BLE connections, latency, and data reception
4. Preliminary field testing	5. Expert validation	Feasibility assessment by sports science and IT experts
5. Main product revision	- (iterative refinement)	Revisions based on expert feedback prior to field deployment
6. Main field testing	6. Field testing & usability	Testing during a 7-versus-7 match simulation and SUS evaluation by coaches
7. Operational product revision	7. Final system refinement	Final bug fixes and system optimization based on field test data
8-10. Final testing & dissemination	- (excluded from scope)	Broad commercial dissemination is beyond the current study scope

Each phase in this adapted framework was conducted sequentially. The test results from a given stage served as the iterative foundation for prototype refinement prior to advancing to the subsequent stage.

System Development

1. Needs Analysis

A needs analysis was conducted to determine the physiological and activity parameters required for monitoring the training load of kabaddi athletes. Based on these requirements, the system was specifically designed to acquire internal load data, namely heart rate (HR). This information was subsequently transmitted wirelessly and presented in numerical and/or graphical formats on the coach dashboard.

2. Hardware

Physiological data acquisition was performed using the Polar H10 sensor (chest strap). The selection of this device was based on its accuracy, utilization of an electrocardiography (ECG) sensor, and its widespread recognition as a wearable device with validated HR measurement. Its validity is well-supported by previous studies in both clinical and sport heart rate monitoring (Protzen et al., 2025; Schaffarczyk et al., 2022).

3. Software and Data Transmission

The system software, named Mohan Pulsehub, was developed to manage the processes of data acquisition, transmission, storage, processing, and visualization. Data from the chest sensors were acquired by the Polar H10 module at an internal ECG sampling frequency of 1000 Hz and transmitted via Bluetooth Low Energy (BLE 5.0) as instantaneous heart rate (HR) packets at an output frequency of 1 Hz (1-second intervals). The central gateway receiver comprised a Raspberry Pi 4 Model B (Broadcom BCM2711 quad-core Cortex-A72 @ 1.5 GHz, 4 GB LPDDR4 RAM, Linux Raspberry Pi OS) equipped with an onboard BLE module and a dedicated local Wi-Fi router (802.11ac, 2.4/5 GHz dual-band). Data packets were processed by a lightweight Python-based local server at an acquisition frequency of 1 Hz and updated continuously on the web-based dashboard interface with a 1 Hz refresh rate.

The system architecture consisted of four primary layers, including (1) the sensing layer, responsible for acquiring physiological and activity data, (2) the communication layer, which transmitted the data via wireless communication, (3) the processing layer, which executed data processing and storage, and (4) the application layer, which presented the information on the dashboard. The dashboard was designed to display key parameters simply and intuitively, allowing coaches to monitor athlete conditions during training without the necessity of manual data analysis.

The received data were uniquely identified using athlete codes and precise timestamps. This timestamping mechanism was highly crucial for evaluating IoT transmission performance, particularly for calculating latency (time delay) from the exact moment the data were recorded by the Polar H10 sensor to when they were visualized on the coach dashboard.

Research Participants

The participants in this study were provincial-level kabaddi athletes actively engaged in a training program. A total of 14 athletes were involved to represent a 7-versus-7 match scenario. This sample size functioned directly as a stress test to evaluate the stability and data transmission performance of 14 Polar H10 sensors operating simultaneously. Inclusion criteria comprised active athletes, full attendance during the simulation session, and a willingness to wear the chest strap device throughout the testing. Conversely, athletes with medical conditions or injuries that posed a risk of impairing physical performance during the testing protocol were excluded from the study.

Prior to data collection, all participants received comprehensive explanations regarding the objectives, procedures, benefits, and potential risks of the study. Subsequently, participants provided written informed consent. The conduct of this research adhered to the ethical principles of sport research and obtained formal ethical approval from Universitas Sultan Ageng Tirtayasa. To maintain the confidentiality of personal and medical data, all participant identities within the system were anonymized using alphanumeric codes.

System Validation Procedure

1. Expert Validation

Content and system feasibility validation were conducted by a panel of four experts, comprising three sports science/sports exercise physiology experts and one information technology/electronics expert. The sports science experts evaluated the appropriateness of physiological parameters, the relevance of training load indicators, data interpretation, and system usability within the context of team sport training. The technology expert assessed hardware aspects, data communication, system stability, user interface, and dashboard functionality.

Each expert assessed the system components using an assessment sheet based on a 1–5 Likert scale. The evaluated aspects encompassed relevance, functional accuracy, ease of use, information readability, and the system suitability for athlete monitoring needs. The evaluation results were utilized to identify system components requiring refinement prior to field testing.

2. Functional Testing

Functional testing was conducted to ensure all system components operated as designed. The testing encompassed the sensor data reading capability, Bluetooth/BLE connection stability, data packet transmission success, continuity of data reception, accuracy of athlete identification, timestamping, data storage, and the dashboard ability to display real-time value changes. Each function was tested iteratively. Any occurrences of data loss, transmission delays, or connection disruptions were recorded.

3. Field and Usability Testing

Field testing was conducted during a 2 × 20-minute 7-versus-7 kabaddi match simulation on a standard indoor court measuring 13 m × 10 m. The central BLE gateway was positioned at mid-court, 2 meters outside the boundary line at an elevated height of 1.5 meters, establishing an operational sensor-to-gateway transmission distance ranging from a minimum of 2.0 meters to a maximum of 9.5 meters. Testing was performed under ambient

indoor environmental conditions (temperature: $28.5^{\circ}\text{C} \pm 1.2^{\circ}\text{C}$, relative humidity: $68\% \pm 4\%$). External wireless interference was maintained under representative field conditions with standard background Wi-Fi network signals present, while all non-essential local Bluetooth devices were deactivated. Throughout the session, the coach utilized the dashboard to monitor the data of the 14 athletes in real-time. This testing aimed to evaluate system functionality in an actual ecological setting. Upon completion of the session, three end users (a head coach, an assistant coach, and a performance analyst) independently evaluated the system ease of use and practicality using the System Usability Scale (SUS) instrument.

Data Analysis

Data analysis was performed using IBM SPSS Statistics software version 26. As the utilized sensor (Polar H10) is a well-recognized wearable device with HR measurement validity supported by previous studies, the analysis in this study did not focus on validating sensor accuracy. Rather, it emphasized the reliability of the IoT transmission system and its usability.

Descriptive analysis was employed to present participant characteristics, the feasibility percentage derived from expert validation and network performance metrics. IoT transmission performance was evaluated based on average latency (in milliseconds) and the percentage of data loss (packet loss) during the match simulation. These data were presented as means, standard deviations, and range values (minimum-maximum).

The system usability level was analyzed based on the System Usability Scale (SUS) questionnaire scores completed by the coaches. The SUS scores were calculated using standard scoring guidelines, ranging from 0 to 100. The system was deemed practical and well-accepted for field implementation if it achieved a minimum SUS score of 68.

Data agreement testing was conducted by comparing synchronized HR time-series datasets recorded by Mohan Pulsehub and the commercial Polar Team application at identical timestamps. Prior to statistical evaluation, the datasets were assigned anonymized code identifiers (Platform A and Platform B) to blind the data analyst to platform identity during ICC, MAE, and Bland–Altman calculations. Data acquisition was performed using Polar H10 sensors transmitting natively at a 1 Hz sampling rate, which were received through a Windows-based central gateway (utilizing a standard x64 processor architecture and the Bluetooth Low Energy protocol) and processed at 1000 ms intervals. The absolute agreement level between the two systems was analyzed using the Intraclass Correlation Coefficient (ICC) with a two-way mixed-effects, absolute agreement model. The visual agreement and mean bias between the two applications were evaluated using Bland-Altman analysis, while the magnitude of transmission error was calculated using the Mean Absolute Error (MAE).

RESULTS

Participant Characteristics

All 14 male provincial-level kabaddi athletes completed the 7-versus-7 match simulation protocol while successfully wearing the Polar H10 devices throughout the data collection process. The demographic and anthropometric characteristics of the participants are presented in Table 2.

Table 2. Participant Characteristics

Characteristics	Results
Number of athletes	14
Gender	Male
Age (years)	20.1 ± 0.8

Characteristics	Results
Age range (years)	19–21
Height (cm)	171.8 ± 5.7
Weight (kg)	68.4 ± 7.2
Training experience (years)	4.1 ± 1.3

Monitoring System Development Results

The development process yielded the Mohan Pulsehub prototype, integrating Polar H10 sensors, a BLE communication module, a local server, and a centralized coach dashboard. Functionally, the system was designed to simultaneously acquire, identify, and display individual athlete data and connection statuses. Table 3 summarizes the system functional test results, demonstrating flawless athlete identification and an extremely high data transmission success rate without permanent connection failures during the stress test.

Table 3. System Functional Test Results

Test Parameter	Results
Tested sensors	14
Successfully connected sensors	14 (100%)
Athlete identification success	100%
Data transmission success	99.72%
Permanent connection failures	0
Dashboard capable of displaying data	100%
Data synchronization disruptions	<1%

Expert Validation

Expert validation was employed to evaluate the system using a structured instrument comprising 25 items distributed evenly across five domains, namely appropriateness of physiological parameters, system functionality, data transmission, dashboard interface, and ease of use. To prevent bias, the four expert validators conducted their assessments independently and were blinded to one another ratings, utilizing a 1–5 Likert scale. Feasibility percentages were calculated, yielding an overall average score of 4.63 out of 5 (92.7%). Furthermore, to establish robust content validity beyond simple mean scores, Aiken’s V statistic was calculated to quantify item- and scale-level validity. The evaluation demonstrated a high degree of inter-rater agreement, with an overall scale-level Aiken’s V of 0.91 (95% CI: 0.83–0.96). Because all item-level V coefficients exceeded the acceptable minimum threshold for four raters, the system content validity was firmly established and it was deemed highly feasible to proceed to the field-testing phase.

Table 4. Expert Validation Results

Evaluated Aspect	Average	Percentage	Category
Appropriateness of physiological parameters	4.67	93.4%	Highly feasible
System functionality	4.75	95.0%	Highly feasible
Data transmission	4.50	90.0%	Highly feasible
Dashboard interface	4.58	91.6%	Highly feasible
Ease of use	4.67	93.4%	Highly feasible
Overall Average	4.63	92.7%	Highly feasible

Real-Time Data Transmission Performance

Transmission performance was evaluated based on latency and packet loss during the simultaneous 14-device match simulation. The metrics presented in Table 5 demonstrate that the system successfully maintained continuous data reception with very low latency and minimal packet loss, confirming its technical stability under multi-user conditions.

Table 5. IoT Transmission Performance

Parameter	Mean $\pm$ SD	Minimum	Maximum
Latency (ms)	186.4 $\pm$ 42.7	112	318
Packet loss (%)	0.28 $\pm$ 0.19	0.02	0.81
Transmission success (%)	99.72 $\pm$ 0.19	99.19	99.98

Furthermore, spatial distance analysis (Figure 1) illustrates the impact of the athlete proximity to the receiver on transmission stability. While overall transmission remained highly successful, minor fluctuations in latency were observed when athletes operated at the furthest edges of the simulation area.

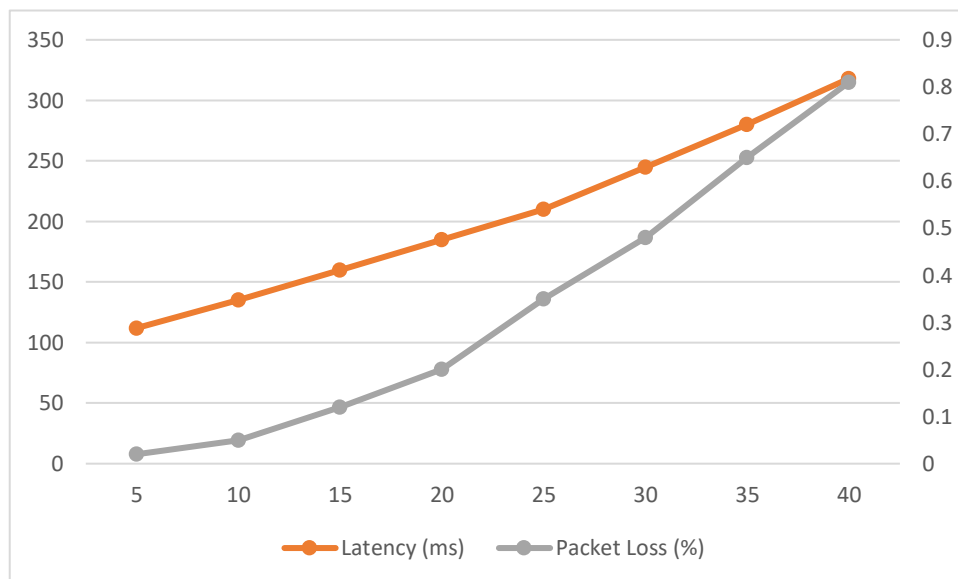


Figure 1. Impact of Spatial Distance on Transmission Latency and Packet Loss

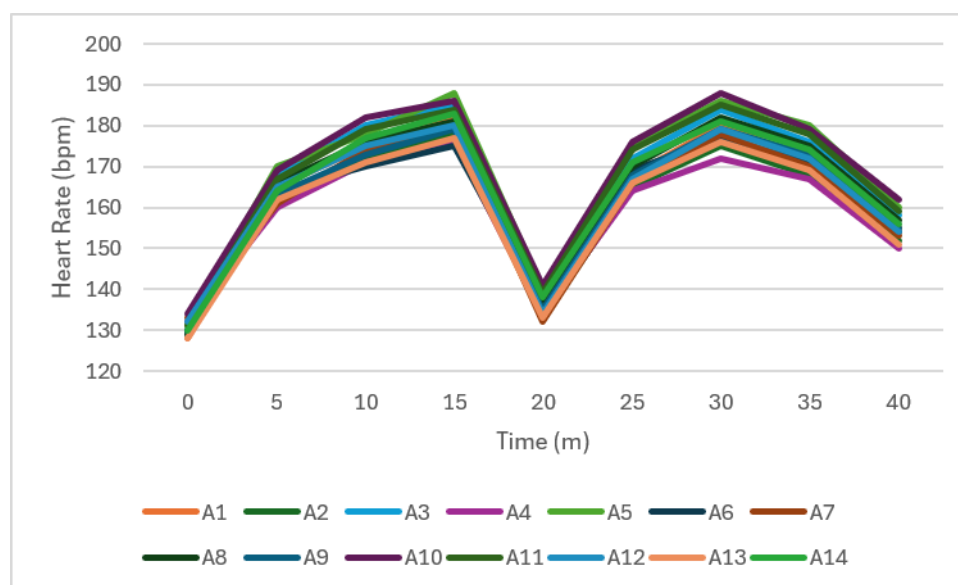
Heart Rate Data Distribution during Simulation

The system continuously captured variations in physiological responses corresponding to the high-intensity and recovery phases of the kabaddi match simulation. Table 6 outlines the distribution of the average heart rates recorded across all athletes. The observed coefficient of variation confirms that the system effectively captured individualized physiological variations during the same simulation protocol.

To complement the statistical distribution, Figure 2 visually presents the continuous real-time heart rate curves across all 14 athletes throughout the 2x20 minute simulation, demonstrating the system capability to simultaneously track individualized intensity peaks and recovery phases.

Table 6. The Athlete Heart Rate Distribution

Parameter	Results
Average HR (bpm)	157.8 ± 11.6
Minimum HR (bpm)	128
Maximum HR (bpm)	188
Median HR (bpm)	158
Coefficient of variation	7.3%

**Figure 2.** Real-Time Heart Rate vs. Time Curves for 14 Simultaneous Active Devices

Heart Rate Data Agreement and Integrity Testing

To verify data integrity during transmission, the HR data recorded on the Mohan Pulsehub dashboard were compared with synchronized output from the benchmark Polar Team application. Statistical agreement metrics are detailed in Table 7. The Intraclass Correlation Coefficient (ICC) and Mean Absolute Error (MAE) indicated a near-perfect absolute agreement, confirming that the developed IoT transmission architecture did not significantly alter the physiological data.

Table 7. Agreement Test Results between Mohan Pulsehub and Polar Team Application

Statistical Parameter	Analysis Result	Interpretation
Intraclass Correlation Coefficient (ICC)	0.998	Very high agreement
95% Confidence Interval (CI) for ICC	0.995 – 0.999	High precision
Mean Absolute Error (MAE)	0.45 bpm	Very low absolute error
Mean Bias (Bland-Altman)	-0.12 bpm	Minimal systematic bias
95% Limits of Agreement (LoA)	-1.35 to 1.11 bpm	Narrow limits of agreement

The visual representation of this agreement is plotted in Figure 3. The Bland-Altman chart visually corroborates the high data integrity, showing that the vast majority of data points fall

well within the narrow limits of agreement (-1.35 to 1.11 bpm) without demonstrating clear proportional bias.

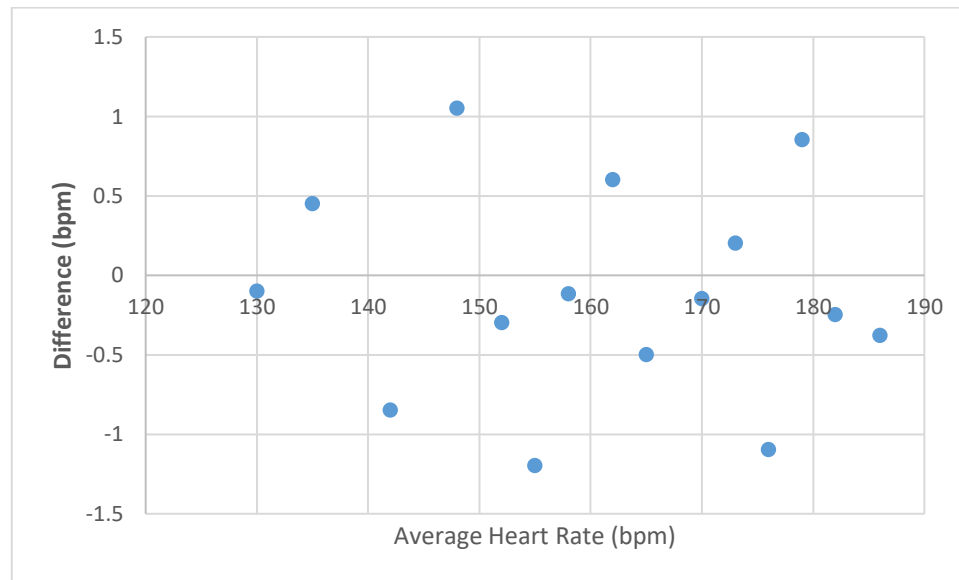


Figure 3. Bland-Altman Agreement Chart Comparing Mohan Pulsehub and The Benchmark Platform

Usability Test Results

Following the simulation, the coaching staff evaluated the system practical implementation. The evaluation yielded a good to excellent System Usability Scale (SUS) score (Table 8), particularly reflecting high ratings for the dashboard capacity to display simultaneous multi-athlete HR information intuitively.

Table 8. System Usability Scale Results

Parameter	Results
Number of users	3
Average SUS score	84.3
SD	5.6
Minimum score	78.8
Maximum score	89.4
Interpretation	Good/Excellent

DISCUSSION

Performance of The Real-Time Physiological Monitoring System

The results indicated that the developed physiological monitoring system was capable of simultaneously acquiring and transmitting heart rate data from 14 athletes with a transmission success rate of 99.72%. The system also yielded an average latency of 186.4 ± 42.7 ms and a packet loss of $0.28 \pm 0.19\%$. These findings demonstrate that the system is not only capable of acquiring physiological data but also of maintaining data continuity when utilized to monitor multiple athletes simultaneously. This is a crucial aspect in the

development of athlete monitoring systems, as the benefits of wearable technology depend not solely on the sensor capability to generate data, but also on the speed, continuity, and accessibility of the data for users (de Beukelaar & Mantini, 2023; Migliaccio et al., 2024; Su et al., 2025).

Recent advancements in sport technology indicate a trend toward continuous, integrated, and data-driven monitoring systems. Wearable technologies are increasingly utilized to acquire physiological and biomechanical information during sporting activities, while IoT technology enables data from various devices to be collected and directly transmitted to a processing system (Olsen et al., 2025; Yang et al., 2024; Zhu et al., 2025). Within this context, the system developed in the present study contributes to the integration aspect by connecting HR sensors with a communication infrastructure and a dashboard accessible to coaches.

These findings are also highly relevant to the demands of team sports. In team sports such as kabaddi, soccer, basketball, or hockey, coaches are required to observe multiple athletes simultaneously. Systems that only display data for a single athlete or necessitate individual device inspection possess practical limitations. Timmerman et al. (2024) highlighted that monitoring systems must be designed according to practitioner needs so that the generated information can genuinely support decision-making. Therefore, the system ability to simultaneously display data for 14 athletes constitutes a significant functional advantage.

Transmission Speed and Real-Time Availability

Operationally, real-time monitoring in sport technology requires instantaneous data transfer. However, since no predefined strict millisecond criterion was established for this study, the system performance is more accurately described as providing near-real-time or low-latency monitoring. The average latency value of 186.4 ms indicates that the system is capable of providing information with a relatively low delay. In HR monitoring, such a delay practically allows coaches to obtain an overview of physiological response changes during training. HR is a physiological parameter whose value changes occur more slowly than network communication speeds. Thus, the system does not require latency at the millisecond level to offer practical benefits in training monitoring.

However, latency cannot be equated with measurement accuracy. Latency denotes the time required for data to travel from the source to the user, whereas validity indicates how close the data are to a reference value. Distinguishing between these two concepts is essential because a system may feature valid sensors but slow transmission, or vice versa. The literature on wearable technology positions measurement accuracy and communication reliability as two distinct aspects requiring separate evaluations (Olsen et al., 2025; Schumann et al., 2025).

The latency variation between 112 and 318 ms indicates that communication performance is not entirely constant. This variation can logically be influenced by the number of active devices, the distance of the sensors from the receiver, Bluetooth/BLE interference, processing loads, and network conditions. The simultaneous use of multiple devices potentially increases transmission queues and generates variations in data reception time. Consequently, future research should evaluate the relationship between the number of active sensors and latency, as well as determining the system maximum capacity.

The packet loss value of 0.28% demonstrates that the vast majority of data were successfully received by the system. From a monitoring perspective, a low data loss rate supports the continuity of physiological information on the dashboard. Nevertheless, the average packet loss does not yet provide an overview of data loss patterns. Random packet

loss entails different consequences compared to sequential data loss during high-intensity activity phases. Therefore, subsequent studies should analyze burst packet loss, the duration of connection disruptions, and the locations where data loss occurs.

Heart Rate Data Agreement and Integrity

The test results demonstrated an ICC value of 0.998 with a 95% CI of 0.995–0.999, an MAE of 0.45 bpm, and a mean bias of -0.12 bpm. The Bland–Altman analysis indicated limits of agreement ranging from -1.35 to 1.11 bpm. Overall, these results indicate a highly robust agreement between the developed system data and the benchmark device. This finding implies that the transmission and visualization processes did not generate substantial alterations to the HR values received by the system.

The utilization of the Polar H10 as the data source is one of the contributing factors to these results. The Polar H10 has been widely employed in sports physiology research and has demonstrated good validity for HR and HRV measurements. Schaffarczyk et al. (2022), for instance, showed that the Polar H10 possesses strong validity under resting conditions and during increasing training intensities. Other studies have also utilized the Polar H10 as a benchmark device in wearable technology testing (O’Grady et al., 2024; Protzen et al., 2025).

The highly substantial ICC value suggests strong absolute agreement. However, validity interpretation should not rely solely on the ICC. The ICC can yield high values when inter-subject variation is large, even in the presence of certain biases. Consequently, the application of the Bland–Altman plot and MAE in this study is crucial as it provides supplementary information regarding the magnitude of actual discrepancies between the systems. Such a combinative approach is recommended in wearable device evaluation, particularly when the devices are used to acquire physiological data that serve as the foundation for decision-making (Schumann et al., 2025).

The MAE result of 0.45 bpm and the near-zero bias signify that the system is capable of preserving HR values during the data transmission process. Nevertheless, these findings must be interpreted with caution. If the system acquires HR from the Polar H10 and is compared with a platform utilizing the exact same measurement source, these results primarily indicate data integrity within the system, rather than the independent validity of the developed sensor. To prove the independent validity of the sensor, future studies should employ a different physiological reference source, such as clinical ECG or an independent reference device.

The System Relationship with Internal Training Load

The average HR of 157.8 ± 11.6 bpm, with a range of 128–188 bpm, illustrates that the system is capable of capturing variations in physiological responses during game simulations. These variations hold significant meaning within the context of internal training load, as athletes engaging in activities within identical game situations do not invariably exhibit identical physiological responses. HR responses are influenced by myriad factors, including aerobic fitness, playing position, activity intensity, recovery status, environmental temperature, hydration, psychological stress, and individual characteristics. Therefore, HR can provide supplementary information concerning how athletes respond to training stimuli, rather than merely documenting the activities performed (Schumann et al., 2025; Spetz et al., 2025).

This concept is paramount in training load management. Training load delineates not only the external work executed by the athlete but also the internal response to that work. Two athletes might perform relatively similar activities yet generate divergent HR responses.

Hence, individualized internal load monitoring can assist coaches in understanding variations in athlete responses and in tailoring training dosages accordingly.

However, the system in this study cannot yet be characterized as a comprehensive training load optimization system. The system primarily supplies HR information as an internal load indicator. In team sports, external load also plays a vital role, encompassing distance covered, speed, acceleration, deceleration, changes of direction, and player load. GPS and IMU technologies have evolved into crucial instruments for acquiring these parameters (Latino & Tafuri, 2024; Sang, 2025; Staunton et al., 2026).

Consequently, the system contribution at this stage is more accurately designated as a real-time internal load monitoring platform. A more comprehensive optimization of training load necessitates the integration of both internal and external loads. This approach aligns with the trajectory of sport technology, which is trending toward the fusion of physiological, biomechanical, and psychological data (Mateus et al., 2025; Su et al., 2025).

Relevance of Multi-Athlete Monitoring in Team Sports

Testing utilizing a 7-versus-7 scenario offers the advantage of evaluating the system with a device count commensurate with actual game situations. Team sports activities possess characteristics distinct from individual training, as they involve intensity fluctuations, explosive movements, physical contact, changes of direction, and interpersonal interactions. Therefore, a system that succeeds under multi-athlete conditions exhibits greater practical relevance compared to a system tested using only a single device.

The literature reveals that wearable technology is increasingly employed in team sports to integrate physiological and kinematic information. Latino & Tafuri (2024) emphasized that the use of sensors can provide a more objective portrayal of athlete physiological responses during sporting activities. Meanwhile, IMU technology can supply information regarding movement characteristics that cannot be obtained exclusively through HR (Zhu et al., 2025).

The system capability to integrate data from 14 athletes into a single dashboard can also alleviate the burden of manual observation. Coaches can concurrently observe HR distributions and identify athletes exhibiting relatively high responses. However, this information must still be interpreted within the context of the game. An athlete with a high HR is not necessarily experiencing fatigue, as HR is also influenced by activity intensity, playing position, environmental conditions, and individual factors.

System Usability

The SUS score of 84.3 ± 5.6 indicates that the system possesses a good to excellent level of usability. These results demonstrate that the system is not only technically operational but also usable by the target end-users. This aspect is crucial, given that the implementation of sport technology heavily relies on its acceptance by coaches and support staff.

Timmerman et al. (2024) stressed that athlete monitoring systems must account for practitioner needs rather than solely focusing on technological capabilities. Overly complex data can augment cognitive load and inadvertently impede decision-making. In the context of this study, the dashboard displaying centralized HR information offers a distinct advantage, as coaches are not required to open or inspect each device individually.

Research by Woolmer et al. (2025) also highlighted the importance of user perception in the implementation of athlete monitoring systems. Athletes and practitioners consider not only the technological benefits but also ease of use, operational burden, and the relevance of the provided information. Therefore, a high SUS score can serve as an initial indication that the system design adequately aligns with user needs.

Nonetheless, the limited number of users constitutes a limitation. Future studies should involve a larger cohort of coaches, performance analysts, strength and conditioning coaches, and sports medical personnel. In addition to the SUS, evaluations could be broadened by employing interviews and task analyses to identify system components that remain challenging for users.

Factors Supporting and Hindering System Performance

The system robust performance was likely supported by several factors. First, the utilization of validated HR sensors reduced uncertainty during the acquisition phase. Second, the number of devices was calibrated to a 7-versus-7 scenario, ensuring the system was tested under multi-athlete conditions. Third, the use of a local network minimized reliance on external internet connections. Fourth, data were presented via a unified dashboard, enabling the concurrent observation of information from all athletes.

From an economic perspective, commercial multi-athlete monitoring ecosystems often require substantial capital expenditure (approximately IDR 45,000,000–75,000,000 initial investment) alongside recurring annual software subscription fees (IDR 7,500,000–18,000,000/year). In contrast, the hardware setup for Mohan Pulsehub utilizing off the shelf Polar H10 sensors (IDR 1,400,000/unit) and an open-architecture Raspberry Pi gateway (IDR 1,200,000) eliminates recurring licensing costs entirely. This represents a reduction of over 60% in initial capital outlay for local sport organizations while providing license-free operational independence.

Conversely, certain factors potentially degraded performance. Signal interference, the distance between sensors and the receiver, the number of devices, spatial structures, other electronic devices, and server loads can all impact latency and packet loss. This explicates why the latency observed in this study did not maintain an entirely constant value.

Beyond technical factors, physiological factors can also influence data interpretation. HR can fluctuate due to both physical activity and non-training factors. Consequently, applying identical HR thresholds for all athletes potentially yields erroneous interpretations. An individualized monitoring approach that incorporates athlete historical profiles is more suitable for long-term system development (Spetz et al., 2025).

Contributions to Scientific Development

The principal contribution of this research lies in the integration of physiological sensors, IoT communication, data validation, and real-time visualization. Research on wearables frequently focuses strictly on sensor validity or the application of sensors for performance measurement. The present study broadens this perspective by situating the communication and data presentation processes as integral components of the monitoring system.

Conceptually, the results indicate that an effective athlete monitoring system necessitates at least three components, including valid data, responsive transmission, and user-friendly information. Accurate but delayed data possess limited decision-making value. Conversely, rapid but invalid data can engender erroneous decisions. Even when both criteria are met, the system must remain comprehensible to the user. This approach aligns with the trajectory of sport technology, which increasingly leans toward the integration of sensors, data analytics, and decision support systems (Mateus et al., 2025; Migliaccio et al., 2024; Włoch et al., 2025). The system developed in this study can serve as a foundation for constructing more complex systems, particularly concerning the integration of internal and external loads.

Study Limitations

This study acknowledges several limitations that warrant consideration. First, the participant cohort was limited to 14 provincial-level male athletes, thereby restricting the generalizability of the results. Future studies should incorporate female athletes, diverse age groups, and athletes of varying performance levels. Second, testing was conducted within a single match simulation scenario. Official match conditions may present more complex communication challenges. Therefore, subsequent research should be conducted longitudinally across multiple training and match sessions.

Third, a major limitation of this study is the lack of independent physiological criterion validity. The agreement analysis compared the developed system with the Polar Team application using the exact same Polar H10 data source. Consequently, this evaluation primarily assessed data transmission and platform software integrity rather than establishing the independent physiological validity of the system itself. Fourth, the system focused solely on HR and has not yet integrated external load parameters. Future iterations could incorporate GPS/GNSS, IMUs, accelerometers, and other kinematic parameters. Such integration would facilitate a more comprehensive analysis of the relationship between external loads and physiological responses (Latino & Tafuri, 2024; Sang, 2025; Staunton et al., 2026).

Fifth, the system has not been extensively tested for scalability. Testing with 14 sensors demonstrated that the system is operational within the employed scenario. However, the maximum number of devices that can be stably monitored remains undetermined. Testing with 20, 30, 40, or more devices could be conducted to establish the system limits. Sixth, usability evaluation was constrained by a limited number of users. Future research must expand the user base and assess the system over long-term usage.

CONCLUSION

This study yielded an IoT-based physiological monitoring system capable of conducting simultaneous and near-real-time heart rate acquisition for 14 athletes. The system demonstrated strong transmission performance and a very high level of software data agreement between the developed system and the benchmark application validation results. Furthermore, a preliminary usability evaluation attained good to excellent initial user acceptance.

Scientifically and practically, this research illustrates the demonstrated technical feasibility of integrating physiological sensors, IoT communication, and dashboards to rapidly provide near-real-time internal load monitoring information in team sports. This framework possesses the immediate potential to assist coaches in concurrently monitoring the physiological responses of multiple athletes without relying entirely on manual observation processes. For practical field deployment, coaching staff should position the central gateway elevated at mid-court within 10 meters of active movement areas and verify device pairing prior to training sessions. Heart rate data on the dashboard should be utilized as a near-real-time supplementary indicator of physiological strain, interpreted alongside tactical demands, player position, and qualitative recovery status rather than serving as an isolated, automated determinant for substitutions or workload adjustments.

Nevertheless, a clear distinction must be made between these demonstrated technical capabilities and outcomes that remain to be established. The current evaluation primarily confirms platform data integrity. It does not yet establish independent physiological criterion

validity, maximum network scalability, or long-term reliability across multiple official matches. Furthermore, comprehensive load monitoring necessitates the future integration of external load parameters, such as distance covered, speed, and player load. Consequently, claims regarding the system direct impact on coaching decision-making, training-load optimization, and actual athletic performance outcomes remain beyond the scope of this initial study. Future research must address these specific gaps through independent validation, larger-scale longitudinal testing, and multimodal data integration to safely evolve this tool into a comprehensive decision-support system.

IMPLICATION

While the present study provides concrete evidence for the feasibility of near-real-time HR transmission, future development could be directed toward multimodal athlete monitoring systems. HR could be integrated with HRV, GPS/GNSS, IMUs, accelerometers, RPE, and recovery indicators. This future integration would enable the system to correlate physiological responses with external work and athlete perception.

The development of analytical algorithms also presents a significant opportunity. Currently, the system functions primarily as a data visualization tool. Future iterations should aim to evolve this capability by generating basic automated alerts based on deviations from individual athlete profiles. Although advanced predictive modeling integrating player tracking and psychophysiological characteristics has shown promise in the broader literature (Teixeira et al., 2025), emphasizing machine learning approaches within this specific system should be deferred until sufficiently large and robust longitudinal datasets are collected to support meaningful model development.

Thus, while the current evidence confirms reliable data transmission, long-term developmental directions should aim not only to enhance transmission speeds but also to augment the system data interpretation capabilities. Subsequent phases could be directed toward decision support systems capable of providing practical insights regarding athlete conditions, training responses, and individual load fluctuation tendencies.

AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

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