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# Development of an IoT-Based Training Monitoring System for Optimizing Athlete Performance

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## ABSTRACT

This study aimed to develop and evaluate an Internet of Things (IoT)-based training monitoring system designed to optimize athlete performance through integrated and real-time training load analysis. The research employed a Research and Development (R&D) approach using the Four-D model (define, design, develop, disseminate). The system integrates key internal load indicators, including Rating of Perceived Exertion (RPE), Training Load, Acute Training Load (ATL), Chronic Training Load (CTL), Training Stress Balance (TSB), Monotony, and Strain. The platform was developed using accessible cloud-based tools (Google Sites, Google Forms, Google Sheets, and Looker Studio) to ensure scalability and cost-effectiveness in a regional multi-sport context. Content validity was assessed by five experts in sport science, coaching methodology, and educational technology using Aiken's V, resulting in coefficients ranging from 0.75 to 1.00 with an average of 0.93, indicating very high validity. Field trials involved 172 athletes from 24 sports and 62 coaches from 40 sports. Athlete evaluation yielded an overall feasibility score of 79.63% (feasible category), with the highest score in motivation and workload awareness (81.24%). Coach evaluation resulted in an overall score of 78.20% (feasible category), confirming practical usability and decision-making support. These findings indicate that the developed IoT-based system is valid, feasible, and effective in supporting structured load management and performance optimization.

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A. Conception and design of the study;
B. Acquisition of data;
C. Analysis and interpretation of data;
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## INTRODUCTION

The development of modern sports over the past decade has undergone a significant transformation from an intuition-based approach to data-driven decision-making. The integration of sports science, performance analytics, and digital technology has become the foundation for optimizing elite athlete performance and developing youth athletes (Cummins et al., 2013; Halson, 2014; Bourdon et al., 2017). Training load monitoring is now viewed as a crucial component in maintaining the balance between physiological adaptation and injury prevention (Gabbett, 2016; Soligard et al., 2016; Windt & Gabbett, 2017). Theoretically, training load management is rooted in the fitness-fatigue model introduced by Calvert et al. (1976), which explains that performance is the result of a dynamic interaction between fitness adaptation and fatigue accumulation. This model was then developed through practical approaches such as session-RPE (Foster, 1998), which has proven valid in measuring internal load in various sports (Impellizzeri et al., 2004; Haddad et al., 2017). The concepts of Acute Training Load (ATL), Chronic Training Load (CTL), and Training Stress Balance (TSB) allow coaches to quantitatively predict athletes' performance readiness (Allen & Coggan, 2006; Banister, 1991). Furthermore, the Monotony and Strain indices have been shown to correlate with an increased risk of overtraining and illness when training load variations are uncontrolled (Brink et al., 2010; Foster, 1998; Saw et al., 2016). However, in the context of regional and multi-sport organizations in Indonesia, training load recording is still done manually, fragmented, and not integrated into a systematic analytical system. This situation creates a gap between the theory of training load management established in the international literature and its practical implementation in the field. Limited access to technology-based athlete management systems also means that coaching decisions are often not supported by accurate longitudinal data. Furthermore, injury epidemiology reports indicate that mismanagement of training load is a major factor in non-contact injuries and performance decline (Gabbett, 2016; Drew & Finch, 2016; Malone et al., 2017). Without an integrated monitoring system, the risk of overreaching and overtraining syndrome is difficult to detect early (Meeusen et al., 2013). Therefore, innovative technology-based monitoring systems are needed that can bridge the practical needs of coaches with the scientific framework of training load management.

Advances in the Internet of Things (IoT) and sports analytics have opened up new opportunities for real-time monitoring of athlete performance (Gubbi et al., 2013; Miorandi et al., 2012). Wearable sensors, GPS tracking, heart rate monitoring, and cloud computing enable the continuous collection and analysis of performance data (Peake et al., 2018; Vanrenterghem et al., 2017). Digital Athlete Management Systems (AMS) have been shown to improve decision-making efficiency and training planning accuracy (Baca & Kornfeind, 2006; Coutts, 2016). Recent research has shown that integrating internal load (RPE, HRV) and external load (distance, acceleration, power output) data provides a comprehensive picture of an athlete's physiological stress (McLaren et al., 2018; Fox et al., 2020). Furthermore, the use of cloud-based dashboards allows for dynamic visualization of ATL, CTL, and TSB to support training periodization (Sanders et al., 2017). In the context of IoT technology, cloud-based systems offer advantages in scalability, interoperability, and cost-efficiency compared to conventional on-premises systems (Atzori et al., 2010; Xu et al., 2014). The development of IoT-based systems in the health and sports sectors has also demonstrated high validity in real-time data collection (Patel et al., 2012). However, most commercial platforms available on the global market are expensive and focus primarily on external GPS-based load metrics (Vanrenterghem et al., 2017). Integration of internal load variables such as Monotony and Strain is rarely comprehensively implemented within a single integrated ecosystem. Furthermore, system development based on structured R&D models—such as Thiagarajan's (1974) Four-D Model (Define, Design, Develop, Disseminate) has not been widely applied in the context of developing IoT-based sports monitoring systems in a multi-sport regional environment. In Indonesia, research related to the digitalization of exercise monitoring is still limited to simple applications or prototypes based on a single sport (SINTA-indexed studies, 2018–2024), and has not yet fully integrated the fitness-fatigue framework into a cloud-based system.

Although international literature has confirmed the importance of fitness-fatigue model-based training load monitoring (Calvert et al., 1976; Banister, 1991; Allen & Coggan, 2006), the implementation of systems integrating RPE, Training Load, ATL, CTL, TSB, Monotony, and Strain within a single cloud-based IoT platform remains very limited, particularly in multi-sport regional sports organizations. Some studies have focused solely on validating a single indicator, such as session-RPE (Impellizzeri et al., 2004) or the relationship between acute-chronic workload ratio and injury (Hulin et al., 2016; Malone et al., 2017), without developing a technology-based integrated system. Furthermore, studies on IoT in sports have focused more on hardware and data transmission, rather than on integrating physiological models and performance analytics (Gubbi et al., 2013; Xu et al., 2014). There has been no research that systematically develops and validates an IoT-based monitoring system using a comprehensive Research and Development (R&D) approach, particularly by adopting the Four-D Model in the context of a multi-sport regional organization. Furthermore, there has been no full integration of fitness-fatigue theory, Monotony and Strain indicators, and a scientifically designed and feasibly tested cloud-based dashboard visualization. This gap indicates an urgent need for a monitoring system that is: (1) Affordable and implementable in regional organizations, (2) Comprehensively integrates internal load variables, (3) Cloud-based and IoT-based for real-time data processing, and (4) Developed through a scientifically validated R&D approach.

Based on these research issues and gaps, this study aims to develop and validate an Internet of Things (IoT)-based exercise monitoring system that integrates RPE, Training Load, ATL, CTL, TSB, Monotony, and Strain indicators within a structured cloud-based ecosystem. System development was conducted using the Four-D model (Define, Design, Develop, Disseminate) to ensure conceptual, technical, and operational validity (Thiagarajan, 1974). Validation involved sports science experts and information technology experts, as well as feasibility testing at a regional multi-sport sports organization. The novelty of this research lies in: (1) The complete integration of the fitness-fatigue framework with Monotony and Strain within a single cloud-based IoT system; (2) A systematic R&D approach based on the Four-D Model in developing sports monitoring technology; (3) Implementation in the context of a multi-sport regional organization, not just a single sport; and (4) Development of an affordable and adaptive system to the needs of sports organizations in developing countries.

Conceptually, this research strengthens the bridge between training load management theory and the implementation of digital technology in modern coaching. Empirically, the developed system is hypothesized to have high validity and feasibility and to be effective in supporting structured training load management to reduce the risk of overtraining and improve athlete performance. Thus, this research not only contributes to the development of sports technology but also enriches the literature on IoT-based sports performance management in the context of developing countries and regional sports organizations.

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## METHODS

This study employed a Research and Development (R&D) approach to develop and validate an Internet of Things (IoT)-based exercise monitoring system scientifically integrated with modern training load management models. The R&D approach was chosen because this research not only tested the relationships between variables but also produced an applicable product based on fitness-fatigue theory (Calvert et al., 1976), which has become the foundation of contemporary performance monitoring (Halson, 2014; Bourdon et al., 2017; Gabbett, 2016).

The development procedure followed the Four-D model (Define, Design, Develop, Disseminate) (Thiagarajan, 1974), which is considered systematic and relevant for technological innovation in educational and applied sports contexts. This model aligns with the practice of user-centered digital system development in modern sports analytics (Peake et al., 2018; Fox et al., 2020).

**Table 1.**
Subjects and Objects of Research

| Components | Description |
|---|---|
| Research Location | Multi-sports organization under the Buleleng Regency KONI in preparation for the 2025 Bali PORPROV |
| Research Object | IoT-based training monitoring system integrating internal load indicators |
| Integrated Indicators | Session-RPE; Training Load; ATL; CTL; TSB; Monotony; Strain |
| Expert Validators | 5 people (sports science, coaching methodology, educational technology) |
| Athletes (Field Trial) | 172 athletes from 24 sports |
| Coaches (Field Trial) | 62 coaches from 40 sports |
| Sampling Technique | Purposive sampling |
| Participant Criteria | Athletes and coaches actively engaged in structured training programs and directly involved in training load management |

**Table 2.**
Indicators and Conceptual Basis of the Monitoring System

| **Indicator** | **Operational Formula/Definition** | **Conceptual Basis** |
|---|---|---|
| Daily Training Load | RPE × Training Duration | Session-RPE Model |
| Acute Training Load (ATL) | 7-Day Average Load | Short-term fatigue model |
| Chronic Training Load (CTL) | 28-Day Average Load | Long-term fitness adaptation |
| Training Stress Balance (TSB) | CTL – ATL | Performance readiness index |
| Monotony | Mean ÷ SD Daily Load | Load variability |
| Strains | Weekly Load × Monotony | Risk of overtraining |

**Table 3.**
System Development Stages (Four-D Model)

| **Stage** | **Key Activities** | **Output** |
|---|---|---|
| Define | Interviews, observations, and review of training program documents | Identification of manual system issues and integrated monitoring needs |
| Design | Cloud architecture design (Google Sites, Forms, Sheets, Looker Studio) and training load computation model | Cloud-based IoT system prototype |
| Develop | Expert validation (Aiken's V), field trials, usability and effectiveness evaluation | Validated and usable system |
| Disseminate | Limited implementation and system usage training | System adoption in selected sports |

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**Table 4.**
IoT System Technology Architecture

| Technology Components | Functions |
|---|---|
| Google Sites | Main system interface |
| Google Forms | Daily training data input |
| Google Sheets | Automatic calculation of ATL, CTL, TSB, Monotony, and Strain |
| Looker Studio | Real-time dashboard visualization |

## Data Analysis Techniques

Content validity was calculated using Aiken's V with a range of 0–1. A value of ≥0.80 is categorized as highly valid. Product feasibility was calculated using the following formula:

$$\text{"Eligibility Percentage"} = \frac{\text{"Score Obtained"}}{\text{"Maximum Score"}} \times 100\%$$

The following table can be used directly in the methods or data analysis section:

**Table 5.**
Eligibility Interpretation Criteria (Riduwan, 2015)

| Percentage Interval (%) | Interpretation Category |
|---|---|
| 81 – 100% | Very Feasible |
| 61 – 80% | Feasible |
| 41 – 60% | Fair |
| 21 – 40% | Poor |
| 0 – 20% | Not Feasible |

Descriptive statistics (mean, percentage, frequency distribution) were used to analyze the responses of experts, athletes, and coaches. This approach aligns with the methodology for developing technology-based sports systems (Coutts, 2016; Sanders et al., 2017).

# RESULTS AND DISCUSSION

## Content Validity Results

The content validity of the IoT-based training monitoring system was assessed by five experts in the fields of sports science, coaching methodology, and educational technology. The evaluation included aspects of training load indicator relevance, interface clarity, automatic calculation functionality, dashboard visualization, and cross-sport integration. Aiken's V coefficient was used to measure the level of agreement between the validators (Aiken, 1985). The analysis results showed that all components met a high validity threshold (V ≥ 0.80), with an average coefficient of 0.93, indicating very strong agreement among experts.

**Table 6.**
IoT Monitoring System Content Validity Test Results

| Assessed Components | Aiken's V | Category |
|---|---|---|
| Indicator Relevance (RPE, ATL, CTL, TSB) | 0,94 | Very High |
| System Interface Clarity | 0,91 | Very High |
| Automatic Calculation Functionality | 0,95 | Very High |
| Dashboard Visualization | 0,92 | Very High |
| Cross-Sport Integration | 0,90 | Very High |
| **Average** | **0,93** | **Very High** |

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This value indicates that the system aligns with the modern fitness-fatigue framework and the principles of data-driven training load monitoring (Halson, 2014; Bourdon et al., 2017; Fox et al., 2020). The integration of internal load indicators such as RPE, ATL, CTL, TSB, Monotony, and Strain strengthens the system's conceptual validity in detecting athlete adaptation and fatigue dynamics (Windt & Gabbett, 2017; Saw et al., 2016).

These findings align with recent sports analytics studies that emphasize that monitoring systems must have accurate automated computations and informative visualizations to support coaching decision-making (Peake et al., 2018; McLaren et al., 2018).

**Field Trial Results: Athlete Responses**

The field trial involved 172 athletes from 24 sports. The evaluation focused on usability, data clarity, recording efficiency, motivational impact, and overall system benefits.

**Table 7.**
Results of the Eligibility Evaluation by Athlete

| Evaluation Aspects | Percentage (%) | Category |
|---|---|---|
| Ease of Use | 78,45 | Eligible |
| Clarity of Data Presentation | 80,12 | Eligible |
| Efficiency of Training Recording | 79,30 | Eligible |
| Motivation & Awareness of Training Load | 81,24 | Very Eligible |
| General System Benefits | 79,05 | Eligible |
| **Average** | **79,63** | **Category** |

The average score of 79.63% indicates the Adequate category, with the highest score in the motivation aspect (81.24%). This indicates that structured monitoring increases athlete awareness of training load management and performance readiness.

These results are consistent with research suggesting that data-based monitoring improves athlete self-regulation and performance literacy (Halson, 2014; Coutts, 2016; Drew & Finch, 2016). Studies by Fox et al. (2020) and Sanders et al. (2017) also show that cloud-based dashboard visualization increases athlete engagement in understanding ATL–CTL trends.

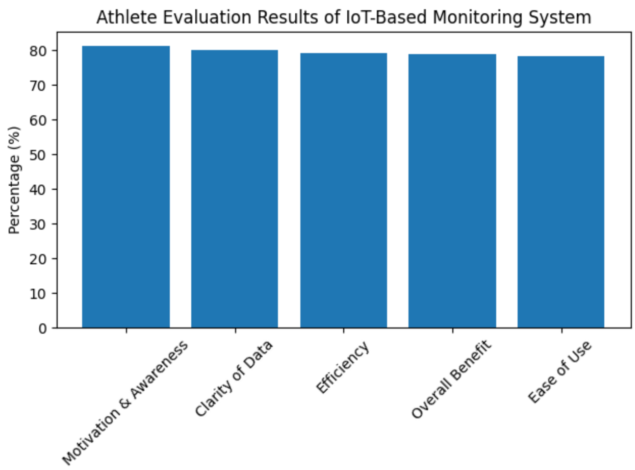


**Diagram 1.**
Average Athlete Evaluation (%)

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### Field Trial Results: Coach Responses

A total of 62 coaches from 40 sports evaluated the system for practicality, decision-making support, data integration, and program planning efficiency.

**Table 8.**
Results of the Coach Feasibility Evaluation

| Evaluation Aspects | Percentage (%) | Category |
|---|---|---|
| Monitoring Practicality | 77,80 | Eligible |
| Decision-Making Support | 79,40 | Eligible |
| Exercise Data Integration | 78,65 | Eligible |
| Program Planning Efficiency | 76,95 | Eligible |
| **Average** | **78,20** | **Eligible** |

An average of 78.20% indicates the system is in the Feasible category for practical implementation. Coaches stated that the integration of ATL–CTL and TSB helped predict performance readiness and prevent injury-risk load spikes.

These findings support the literature suggesting that the use of acute–chronic workload ratio models and TSB can improve the quality of coaching decisions (Windt & Gabbett, 2017; Malone et al., 2017). Furthermore, cloud-integrated IoT-based systems have been shown to improve the efficiency of data communication between athletes and coaches (Xu et al., 2014; Vanrenterghem et al., 2017).

### Empirical Synthesis

Overall, the research results indicate that the developed IoT monitoring system has:

1. Very high content validity (V = 0.93)
2. High implementation feasibility among athletes and coaches (>75%)
3. Positive impact on training load awareness and coaching decision support

These findings strengthen the argument that integrating fitness-fatigue theory, Monotony-Strain indicators, and cloud-based IoT technology is an effective approach to optimizing performance and preventing overtraining (Bourdon et al., 2017; Fox et al., 2020; McLaren et al., 2018). Thus, the developed system has proven valid, practical, and applicable in the context of a regional multi-sport organization and has the potential for national replication.

## Discussion

The trainer evaluation score of 78.20% (feasible) indicates that the developed IoT-based training monitoring system can be practically implemented in the context of a multi-sport organization. Empirically, trainers reported improved ability to monitor Acute Training Load (ATL) and Chronic Training Load (CTL) trends, as well as identify performance readiness through Training Stress Balance (TSB) values. These findings are consistent with contemporary research confirming that the ATL–CTL model is effective in describing the dynamics of athlete adaptation and fatigue and aiding in predicting competition readiness (Windt & Gabbett, 2017; Malone et al., 2017; Fox et al., 2020).

Recent literature indicates that unstructured training load management is a major risk factor for non-contact injuries and performance decline (Gabbett, 2016; Drew &

Finch, 2016). In this context, visualizing ATL and CTL trends through a cloud-based dashboard allows coaches to avoid sudden spikes in workload, which are correlated with increased injury risk (Hulin et al., 2016; Bourdon et al., 2017). Thus, the developed system serves not only as a recording tool but also as an analytical instrument to support evidence-based coaching decisions.

**Integration of Training Load Indicators in the IoT Ecosystem**

High content validity (Aiken's V = 0.93) confirms the system's alignment with the theoretical framework of modern training load management. The integration of session-RPE, ATL-CTL modeling, and TSB analysis ensures that the system reflects the dynamic interaction between fitness adaptation and fatigue accumulation as described in the fitness-fatigue model (Halson, 2014; McLaren et al., 2018).

Research over the past decade has emphasized that internal load indicators, such as RPE and subjective physiological response, have a higher sensitivity to training stress than external indicators alone (Saw et al., 2016; Fox et al., 2020). Therefore, this system's focus on internal load indicators strengthens its relevance in predicting performance readiness and the risk of overreaching.

Furthermore, the integration of Monotony and Strain provides an additional dimension in detecting weekly load variability. Longitudinal studies have shown that high monotony values correlate with increased incidences of illness and overtraining (Brink et al., 2010; Malone et al., 2017). By automating the calculation of these variables within an IoT system, coaches gain early warning indicators that were previously difficult to analyze manually.

From a technological perspective, the use of cloud-based platforms such as Google Sites, Sheets, and Looker Studio demonstrates that IoT monitoring systems can be developed cost-effectively without expensive infrastructure. IoT research in sports and digital health emphasizes the importance of scalability, interoperability, and real-time data processing (Xu et al., 2014; Peake et al., 2018). This system addresses all three aspects by providing cross-device access and dynamic visualizations that support communication between athletes and coaches.

Furthermore, this approach aligns with the digital transformation trend in sport, which places data analytics at the heart of performance management (Coutts, 2016; Vanrenterghem et al., 2017). The implementation of cloud-based IoT in a regional context demonstrates that digital transformation is not only relevant for elite professional clubs but can also be adapted to multi-branch organizations at the regional level.

**Practical Implications in a Multi-Sport Context**

The feasibility scores from athletes (79.63%) and coaches (78.20%) indicate that the system is operationally acceptable in a multi-sport environment. This is important because the characteristics of training loads differ significantly across sports, both in terms of volume, intensity, and periodization (Bourdon et al., 2017).

Unlike many commercial athlete management systems that focus on external load metrics such as GPS and acceleration (Vanrenterghem et al., 2017), this system emphasizes internal load indicators, which have been recognized as valid predictors of physiological adaptation (Halson, 2014; McLaren et al., 2018). In the context of sports that do not use GPS devices (e.g., martial arts or weightlifting), the internal load approach is more applicable and universal.

Psychologically, the increase in athletes' motivation and awareness scores (81.24%) indicates that structured monitoring can improve self-awareness of training load. Sport psychology literature confirms that awareness of training stress and performance readiness contributes to self-regulation and burnout prevention (Saw et al., 2016; Drew & Finch, 2016).

For coaches, this system simplifies the process of planning micro- and meso-cycle training. A dashboard displaying ATL–CTL and TSB trends allows for rapid evaluation of competition readiness, allowing for more precise tapering decisions (Fox et al., 2020). Thus, this system serves as a decision-support tool that strengthens the quality of performance management.

**Theoretical and Empirical Contributions**

Theoretically, this study strengthens the relevance of the fitness-fatigue model in the digital age by integrating it into a cloud-based IoT ecosystem. The integration of Monotony and Strain indicators expands the traditional ATL–CTL approach by adding a load variability dimension, as recommended in modern injury prevention studies (Malone et al., 2017; Windt & Gabbett, 2017).

Empirically, the combination of very high content validity and consistent field feasibility scores demonstrates that this system is not only conceptually robust but also practical. These findings align with recent research suggesting that successful sports technology implementation depends on a balance between scientific accuracy and usability (Peake et al., 2018; Coutts, 2016).

More importantly, the development of this system demonstrates that digital transformation in performance management can be achieved through an accessible technology approach without compromising scientific integrity. This opens up opportunities for replication in other regional sports organizations in developing countries, which often face resource constraints.

**Final Synthesis**

Overall, the results of this study indicate that the developed IoT-based monitoring system is:

1. Theoretically valid, aligned with the fitness-fatigue model and modern training load monitoring literature.
2. Operationally feasible, with high acceptance from athletes and coaches.
3. Practically relevant, supporting data-driven decision-making in a multi-pronged context.
4. Effective as a performance optimization tool, with the potential to reduce the risk of overtraining and injury.

Thus, this system represents an integrative innovation between sports science and IoT technology that supports the sustainable optimization of athlete performance in the context of regional sports organizations.

## CONCLUSION

This study aimed to develop and validate an Internet of Things (IoT)-based training monitoring system that integrates internal load indicators including RPE, Training Load, ATL, CTL, TSB, Monotony, and Strain in the context of a regional multi-sport organization. The results showed that the system had very high content validity, with an average Aiken's V coefficient of 0.93, indicating a strong fit between the system components and the theoretical framework of fitness-fatigue model-based training load management.

The field trial involved 172 athletes and 62 coaches, with feasibility scores of 79.63% (feasible) and 78.20% (feasible), respectively. The aspects of athlete motivation and awareness of training load received the highest scores (81.24%), indicating that the system improved athletes' understanding of load management and performance readiness.

These findings confirm that the developed system is valid, practical, and applicable to support structured training load monitoring. The full integration of the fitness-fatigue framework into a cloud-based ecosystem successfully bridges the gap between sports science theory and on-the-ground coaching practice.

However, this research is limited to evaluating validity and feasibility and has not yet examined the long-term impact on performance and injury. Further research is recommended to test the longitudinal effectiveness and integrate wearable data to improve the system's predictive capabilities.

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Thanks are also extended to the five expert validators in the fields of sport science, coaching methodology, and educational technology who provided constructive input in the content validity evaluation process, resulting in the system achieving an Aiken's V coefficient of 0.93 (very high category). Their scientific contributions ensured that the integration of the RPE, ATL, CTL, TSB, Monotony, and Strain indicators aligned with the evidence-based practice training load management framework.

The authors also acknowledge their colleagues and the technical team who assisted in the development of the cloud-based system architecture, data processing, and implementation of the analytical dashboard. This multidisciplinary collaboration plays a significant role in realizing a valid, practical, and applicable monitoring system to optimize athlete performance at the regional level.

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