Artificial Intelligence-Based Training Load Monitoring and Injury Prevention in Youth Athletes: A Sports Science Perspective

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Abstract

Objectives: This study aimed to examine the effectiveness of Artificial Intelligence (AI)-based monitoring systems in optimizing training load management and reducing injury risk among youth athletes.
Materials and Methods: This study used a mixed-method approach by combining quantitative data obtained from wearable devices with qualitative information collected from coaches and sports science practitioners. The quantitative component focused on training load, fatigue indicators, and injury-risk signals, while the qualitative component explored the practical use of AI-based systems in training decision-making.
Results: The findings indicate that AI-based monitoring systems can provide more accurate and real-time analysis of athlete workload. These systems support the early detection of fatigue, excessive training load, and potential injury-risk factors. In addition, AI-based monitoring helps coaches design more individualized training programs based on the physiological and biomechanical characteristics of each athlete.
Conclusions: AI-based training load monitoring has the potential to improve performance management and reduce injury risk in youth athletes. Its use can support safer, more personalized, and evidence-based training practices in youth sports development. Future studies are recommended to examine long-term implementation, data privacy, and ethical considerations in the use of AI in sports training.

Keywords: Artificial Intelligence, training load, injury prevention, youth athletes, sports science

Introduction

Youth athlete development is a multidimensional process that requires an appropriate balance between training stimulus, recovery, biological maturation, and long-term performance progression (Bergeron et al., 2024; Cobley et al., 2014; Jayanthi et al., 2022). During adolescence, athletes experience rapid changes in musculoskeletal structure, neuromuscular coordination, hormonal regulation, and psychological readiness (Condello et al., 2019; Fogelholm et al., 1992; Kuswoyo et al., 2020). These developmental characteristics make youth athletes highly responsive to training adaptations, but also more vulnerable to injury when training load is not properly monitored. Excessive or poorly managed training load has been associated with fatigue accumulation, reduced performance capacity, overuse injuries, and increased risk of musculoskeletal problems, particularly in athletes whose growth plates, tendons, and joint structures are still developing(Travers & Muri Irland, 2024).

In youth sports settings, training programs are often designed to improve technical skills, physical fitness, tactical awareness, and competitive performance within a relatively short period. However, the pursuit of rapid performance improvement may lead to inappropriate increases in training volume, intensity, and competition frequency(Bergeron et al., 2015; Penggalih et al., 2025; Santos et al., 2024). When external load, such as running distance, acceleration, deceleration, jumping frequency, or total training duration, is not aligned with internal load, such as heart rate response, perceived exertion, fatigue, and recovery status, athletes may experience maladaptation. Therefore, training load monitoring plays an important role in ensuring that training demands remain within a safe and productive range.

Traditional approaches to monitoring training load, including session rating of perceived exertion, training diaries, coach observation, and periodic fitness testing, have been widely used in sports practice(Bompa et al., 2009; Penggalih et al., 2025). Although these methods are practical and accessible, they have several limitations. They often rely on subjective judgment, delayed evaluation, and incomplete information about the athlete’s physiological and biomechanical responses. Coach observation, for example, may identify visible signs of fatigue but may not detect subtle neuromuscular changes or early physiological stress. Similarly, session rating of perceived exertion provides useful information about perceived training difficulty, but it cannot fully capture complex interactions between fatigue, movement quality, recovery, and injury risk.

The rapid development of Artificial Intelligence has created new opportunities for improving training load monitoring and injury prevention in sports science. AI-based systems are able to process large and complex datasets obtained from wearable devices, motion sensors, global positioning systems, force platforms, and athlete management systems. Through machine learning algorithms, these systems can identify patterns that may not be easily detected through conventional observation. Variables such as heart rate variability, movement asymmetry, acceleration load, jump mechanics, sleep quality, recovery status, and fatigue indicators can be analyzed simultaneously to provide more accurate and individualized information about athlete readiness and injury risk.

The integration of AI with wearable technology is particularly relevant in youth sports because it allows continuous and real-time monitoring during training and competition. Instead of relying only on post-training evaluation, coaches and sports scientists can receive immediate feedback regarding excessive workload, abnormal movement patterns, declining recovery status, or potential injury-risk signals. This information can support evidence-based decision-making, such as adjusting training intensity, modifying recovery strategies, reducing repetitive mechanical stress, or individualizing training programs according to each athlete’s physiological and biomechanical characteristics. In this context, AI does not replace the role of coaches, but strengthens coaching decisions by providing objective and data-driven insights.

Despite these advantages, the implementation of AI-based monitoring in youth sports remains limited and requires further investigation. Most existing applications of AI in sport have focused on elite adult athletes, professional clubs, or high-performance environments with advanced technological resources. In contrast, youth sports programs often face challenges related to cost, accessibility, data interpretation, coach readiness, ethical use of athlete data, and privacy protection. Furthermore, because youth athletes are still undergoing biological and psychological development, AI-based recommendations must be interpreted carefully and should consider maturation status, training age, growth-related changes, and the educational purpose of youth sport.

Therefore, this study aims to examine the role of AI-based training load monitoring in supporting injury prevention and performance optimization among youth athletes.

Specifically, this study focuses on how AI-integrated monitoring systems can analyze training load, detect fatigue-related risk factors, and assist coaches in designing safer and more individualized training programs. By addressing this issue, the study contributes to the development of evidence-based youth sport practices that prioritize both athletic performance and long-term athlete health.

Materials and Methods

Research Design

This study employed a mixed-method research design that combined quantitative and qualitative approaches to obtain a comprehensive understanding of the implementation of Artificial Intelligence (AI)-based training load monitoring in youth athletes. The quantitative component was used to examine changes in training load indicators, fatigue response, and injury-risk scores during the intervention period. Meanwhile, the qualitative component explored the perceptions of coaches and athletes regarding the usability, practicality, and perceived effectiveness of the AI-based monitoring system in daily training practice.

The mixed-method design was selected because AI-based monitoring in sports cannot be evaluated only through numerical performance and physiological indicators, but also requires contextual information related to user experience, coach decision-making, athlete compliance, and practical challenges during implementation.

Study Participants

The participants of this study were 60 youth athletes aged 13–17 years who were actively involved in structured training programs. The athletes were recruited from three sports disciplines, namely football, basketball, and athletics. Participants were selected using purposive sampling based on specific inclusion criteria.

The inclusion criteria were as follows: athletes aged between 13 and 17 years, actively participating in organized training at least three times per week, having a minimum of one year of training experience in their respective sport, being physically able to participate in regular training sessions, and obtaining permission from parents or guardians. Athletes were excluded if they had acute injuries, chronic musculoskeletal disorders, cardiovascular problems, or other medical conditions that could interfere with training participation or affect the accuracy of physiological monitoring.

All participants and their parents or guardians were informed about the objectives, procedures, potential risks, and confidentiality of the study. Participation was voluntary, and athletes were allowed to withdraw from the study at any stage without penalty.

Study Organization

The study was conducted over an 8-week training period. During this period, athletes continued their regular training programs under the supervision of their respective coaches. The AI-based monitoring system was integrated into the training process to collect, process, and interpret training load data.

Before data collection, athletes and coaches received an orientation session regarding the use of wearable devices, data recording procedures, and the interpretation of AI-generated reports. Baseline data were collected during the first week to identify initial workload patterns, fatigue indicators, and injury-risk profiles. After the baseline phase, athletes wore monitoring devices during each training session throughout the intervention period.

The wearable devices recorded physiological and movement-related data, including heart rate, heart rate variability, training duration, movement intensity, distance covered, acceleration, deceleration, and workload patterns. These data were automatically transferred to the AI-based monitoring platform. The AI system used machine learning algorithms to analyze individual training responses and generate reports related to workload, fatigue status, and potential injury-risk signals.

The AI-generated reports were reviewed by coaches and sports science practitioners to support training decisions. When the system identified excessive workload, abnormal fatigue patterns, or increased injury-risk indicators, coaches were encouraged to adjust training intensity, recovery strategies, or session structure. These adjustments were made to ensure that training remained safe, individualized, and appropriate to the athlete's readiness condition.

In addition to quantitative monitoring, questionnaires and semi-structured interviews were conducted with coaches and athletes at the end of the intervention period. These instruments were used to explore their perceptions of the AI system, including ease of use, usefulness, accuracy of feedback, influence on training decisions, and practical challenges during implementation.

Research Instruments

Several instruments were used in this study:

1. Wearable Devices
Wearable devices were used to collect physiological and biomechanical data during training sessions. The recorded variables included heart rate, heart rate variability, movement distance, acceleration, deceleration, training duration, and workload intensity. These indicators were used to describe both internal and external training load.

2. AI-Based Monitoring System
The AI-based monitoring system was used to process data obtained from wearable devices. Machine learning algorithms analyzed workload patterns, fatigue responses, and injury-risk indicators. The system generated individual reports that provided information about athlete readiness, excessive load, and potential risk of injury.

3. Training Load and Fatigue Questionnaire
A questionnaire was used to assess athletes' perceived fatigue, recovery status, muscle soreness, sleep quality, and perceived training difficulty. This instrument helped complement the objective data collected from wearable devices.

4. Semi-Structured Interviews
Semi-structured interviews were conducted with coaches and selected athletes to obtain qualitative information regarding the practical implementation of the AI-based monitoring system. The interview focused on usability, perceived benefits, limitations, and the role of AI-generated feedback in training decision-making.

Data Collection Procedures

Data collection was conducted in several stages. First, participants were screened based on the inclusion and exclusion criteria. Second, eligible athletes and their parents or guardians provided informed consent. Third, baseline measurements were conducted to obtain initial data on training load, fatigue level, and injury-risk indicators.

During the 8-week observation period, athletes wore monitoring devices in every training session. The collected data were processed by the AI monitoring system in real time. Coaches received workload and fatigue reports that could be used to adjust training plans when necessary. At the end of the study, post-intervention data were collected to compare changes in injury-risk indicators and training load response.

Qualitative data were collected through questionnaires and interviews after the completion of the intervention. The responses were used to support the interpretation of quantitative findings and to understand the practical value of AI-based monitoring in youth sport settings.

Statistical Analysis

Quantitative data were analyzed using descriptive and inferential statistics. Descriptive statistics, including mean, standard deviation, frequency, and percentage, were used to describe participant characteristics, training load indicators, fatigue levels, and injury-risk scores.

Before inferential analysis, the normality of the data distribution was examined using the Shapiro–Wilk test. If the data were normally distributed, paired sample t-tests were used to compare pre- and post-intervention injury-risk scores and fatigue indicators. If the data were not normally distributed, the Wilcoxon signed-rank test was used as a non-parametric alternative. The level of statistical significance was set at $p < 0.05$.

Qualitative data from interviews were analyzed using thematic analysis. The analysis involved data familiarization, coding, theme identification, theme review, and interpretation. The qualitative findings were used to explain the practical experiences of coaches and athletes in using AI-based monitoring systems and to strengthen the interpretation of the quantitative results.

Ethical Considerations

This study was conducted in accordance with ethical principles for research involving human participants. Since the participants were minors, written informed consent was obtained from parents or guardians, and assent was obtained from the athletes. Participant confidentiality was maintained by coding all personal data and ensuring that the collected information was used only for research purposes. Data from wearable devices and AI systems were stored securely to protect athlete privacy.

Results

The implementation of the AI-based monitoring system demonstrated positive effects on training load management, fatigue detection, injury-risk prediction, and user acceptance among youth athletes. The results showed that AI-based monitoring provided more accurate workload assessment compared with traditional coach-based observation and session rating of perceived exertion. In addition, predicted injury-risk scores decreased after the 8-week monitoring period, indicating that real-time workload feedback and fatigue alerts helped coaches adjust training intensity and recovery strategies more effectively.

Training Load Accuracy

The AI-based monitoring system showed higher training load accuracy compared with traditional monitoring methods. The mean accuracy score of traditional monitoring was 74.20 ± 6.85, while the AI-based system reached 88.60 ± 5.14. The difference was statistically significant ($p = 0.001$), indicating that AI-based systems provided more precise and objective workload measurements.

Table 1. Comparison of Training Load Monitoring Accuracy

Monitoring Method	Mean Accuracy Score	SD	p-value
Traditional monitoring	74.20	6.85	0.001
AI-based monitoring	88.60	5.14	

Injury Risk Reduction

A significant reduction in predicted injury-risk scores was observed after the implementation of the AI-based monitoring system. The mean injury-risk score decreased from **42.50 ± 8.40** before the intervention to **27.10 ± 6.90** after the intervention. This reduction was statistically significant **($p = 0.002$)**, suggesting that AI-based monitoring supported early identification of excessive training load and potential injury-risk factors.

Table 2. Pre- and Post-Intervention Injury-Risk Scores

Variable	Pre-intervention	Post-intervention	Mean Difference	p-value
Predicted injury-risk score	42.50 ± 8.40	27.10 ± 6.90	15.40	0.002

Fatigue Detection

The AI algorithm successfully identified early signs of fatigue based on changes in heart rate variability, workload intensity, movement patterns, and recovery indicators. The system showed good detection performance, with a fatigue detection sensitivity of **86.70%** and specificity of **82.40%**. These findings indicate that the AI-based system was able to detect fatigue-related warning signs before they developed into performance decline or injury risk.

Table 3. AI-Based Fatigue Detection Performance

Indicator	Percentage
Sensitivity	86.70%
Specificity	82.40%
Overall detection accuracy	84.50%

User Feedback

The qualitative findings showed that coaches and athletes perceived the AI-based monitoring system positively. Coaches reported that real-time feedback increased their confidence in adjusting training intensity, planning recovery sessions, and identifying athletes at risk of overload. Athletes also reported better awareness of their fatigue status and improved adaptation to training demands.

Table 4. User Feedback on AI-Based Monitoring

User Group	Main Feedback	Interpretation
Coaches	Increased confidence in training decisions	AI feedback helped adjust workload and recovery
Athletes	Better awareness of fatigue and recovery	Athletes became more responsive to training demands
Sports practitioners	Easier identification of overload risk	AI reports supported injury-prevention strategies

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Figure 1. Training Load Accuracy: Traditional vs AI-Based Monitoring

Method	Score
Traditional monitoring	74.20
AI-based monitoring	88.60

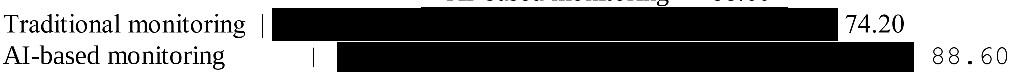

Figure 2. Reduction in Predicted Injury Risk

Phase	Injury-Risk Score
Pre-intervention	42.50
Post-intervention	27.10

The results of this study indicate that AI-based monitoring systems contributed to improved training load management and injury prevention among youth athletes. The AI-based system demonstrated higher workload measurement accuracy **(88.60 ± 5.14)** compared with traditional monitoring methods **(74.20 ± 6.85)**, with a statistically significant difference **(p = 0.001)**. In addition, the predicted injury-risk score decreased from **42.50 ± 8.40** before the intervention to **27.10 ± 6.90** after the intervention **(p = 0.002)**. These findings suggest that real-time AI-based feedback helped identify excessive workload and fatigue-related risk factors earlier.

The AI algorithm also showed good performance in detecting fatigue, with sensitivity of **86.70%**, specificity of **82.40%**, and overall detection accuracy of **84.50%**. Qualitative feedback further supported the quantitative findings. Coaches reported greater confidence in making training decisions, especially in adjusting workload intensity and recovery strategies. Meanwhile, athletes reported better awareness of fatigue and improved adaptation to training demands. Overall, the findings demonstrate that AI-based monitoring can support safer, more individualized, and evidence-based training management in youth sports.

Discussion

The findings of this study indicate that AI-based training load monitoring provides meaningful advantages over conventional monitoring approaches in youth athlete development(Alamäki et al., 2024; Penggalih et al., 2025). The use of AI-supported systems allowed training load, fatigue indicators, and injury-risk signals to be analyzed more accurately and continuously. Compared with traditional methods such as coach observation and session rating of perceived exertion, AI-based monitoring offers a more objective and individualized interpretation of athlete responses. This is particularly important in youth sports, where athletes may differ in biological maturation, training history, recovery capacity, and physiological adaptation.

One of the main strengths of AI-based monitoring is its ability to process large and complex datasets in real time. In practical training settings, athlete performance is influenced by several interacting factors, including internal load, external load, recovery status, movement quality, and fatigue accumulation. Conventional approaches often evaluate these factors separately and retrospectively. In contrast, AI systems can integrate multiple variables, such as heart rate response, movement intensity, acceleration patterns, workload changes, and fatigue indicators, to provide a more complete picture of athlete readiness. This supports coaches in designing training programs that are not only performance-oriented but also responsive to each athlete's current condition.

The predictive capability of AI is another important contribution to injury prevention. Rather than waiting until athletes show visible signs of injury or performance decline, AI-based systems can identify early patterns associated with excessive workload and fatigue. This enables coaches to apply proactive strategies, such as reducing training intensity, modifying drills, extending recovery periods, or providing individualized load adjustments. In this context, AI-based monitoring supports a shift from reactive injury management to preventive training management. This approach is consistent with contemporary sports science principles that emphasize the importance of load regulation, fatigue control, and recovery planning in reducing injury risk(Dowling et al., 2014; Thomson et al., 2015).

The results also suggest that AI-based monitoring may improve decision-making quality among coaches. Real-time feedback can help coaches move beyond subjective judgment and make training decisions based on objective data. This does not mean that AI replaces coaching experience. Instead, AI functions as a supporting tool that strengthens the coach's ability to interpret athlete condition and adjust training appropriately. In youth sports, this is highly relevant because training decisions should consider not only performance outcomes but also long-term athlete development, growth-related vulnerability, and safe participation.

Furthermore, the positive feedback from athletes indicates that AI-based monitoring may increase athlete awareness of fatigue, recovery, and training adaptation. When athletes understand their workload and recovery status, they may become more engaged in managing their own training behavior. This can encourage better communication between athletes and coaches, especially regarding tiredness, discomfort, sleep quality, and perceived readiness. Therefore, AI-based monitoring may contribute not only to injury prevention but also to athlete education and self-regulation(Alamäki et al., 2024; Penggalih et al., 2025).

Despite these advantages, several challenges should be considered. The implementation of AI-based monitoring requires adequate technological infrastructure, reliable wearable devices, stable data systems, and personnel who are able to interpret the results correctly. Without proper understanding, AI-generated reports may be misinterpreted or used too rigidly. In addition, youth sports programs may face limitations related to cost, accessibility, and coach readiness. These issues are important because the effectiveness of AI does not depend only on the technology itself, but also on how the system is integrated into daily training practice.

Ethical considerations are also central in the use of AI for youth athlete monitoring. Since the participants are minors, data privacy, informed consent, and responsible data management must be prioritized. Athlete monitoring should not create excessive pressure, reduce autonomy, or be used to label young athletes negatively based on predicted risk scores. AI-based data should be used to support athlete welfare, not to punish or exclude athletes from participation. Therefore, clear guidelines are needed regarding data ownership, confidentiality, parental consent, and appropriate use of predictive information.

The findings of this study are consistent with previous research showing that wearable technology and machine learning can improve performance monitoring, workload interpretation, and injury-risk identification in sports. However, this study extends the discussion by emphasizing the practical relevance of AI-based monitoring in youth athletes. Unlike adult or elite athletes, youth athletes require a more cautious and developmentally appropriate approach because their physiological and psychological characteristics are still changing. Therefore, AI-based recommendations should always be interpreted together with coach judgment, medical considerations, and the athlete's developmental stage.

Overall, the results suggest that AI-based training load monitoring can support safer, more individualized, and evidence-based training management in youth sports. Its value lies not only in improving data accuracy, but also in helping coaches recognize early fatigue signs, prevent excessive workload, and optimize performance development. Nevertheless, further research is needed to examine the long-term effects of AI-based monitoring on injury incidence, athletic performance, psychological readiness, and coach-athlete interaction across different sports disciplines and competitive levels.

Conclusion

Artificial Intelligence-based training load monitoring is an effective tool for supporting performance optimization and injury prevention in youth athletes. By providing real-time and individualized data, AI systems help coaches manage training load more precisely, detect early signs of fatigue, and reduce potential injury risks.

The integration of AI in youth sports programs is recommended as a supportive tool for evidence-based coaching, provided that data privacy, informed consent, and proper implementation are carefully considered. Future studies should use longitudinal designs and include psychological, environmental, and sport-specific factors to improve the accuracy of AI-based monitoring models.

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