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Smarter, Faster, Safer: How AI Is Rewiring Sports, Performance Science, and Athlete Health

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Abstract

Background. Artificial intelligence (AI) is rapidly permeating sports medicine and performance science, propelled by high-volume data from wearables, video, and clinical systems. Beyond traditional analytics, modern machine learning (ML) and deep learning (DL) can model complex, nonlinear relationships to support diagnosis, injury prevention, load management, and tactical decisions. Yet adoption remains uneven due to concerns about data quality, bias, interpretability, governance, and the appropriate balance between automation and expert judgment.

Aim. To synthesize emerging evidence on AI applications across sports medicine and performance optimization, clarifying opportunities, constraints, and ethical considerations required for safe, effective, and equitable integration.

Material and methods. Narrative review of AI modalities, core data ecosystems and representative use cases spanning MSK imaging, injury-risk modeling, movement analysis, recovery optimization, and tactical decision support. The review emphasizes multimodal data fusion, model oversight, and real-world implementation factors.

Current State of Knowledge. Evidence indicates AI can enhance diagnostic speed and accuracy in MSK imaging, improve early detection of overuse and acute injury risk via spatiotemporal and physiological signals. enable individualized load management and adaptive training through time-series modeling; and support coaching and education via NLP and LLM-powered tools. Key limitations include dataset heterogeneity, biased sampling and gaps between prototype performance and field deployment.

Conclusions. AI can make training and care more precise, proactive, and accessible, but benefits hinge on high-quality data pipelines, transparent models, clinician/coach oversight, and ethical safeguards. Interdisciplinary collaboration is essential to realize performance gains while protecting athlete welfare and equity.

Key words: artificial intelligence; machine learning; deep learning; sports medicine; performance optimization; injury prevention; rehabilitation; wearables; multimodal data

1. Introduction and purpose

Artificial intelligence (AI) has become an increasingly transformative force across clinical medicine, public health, and human performance domains. In recent years, the sports industry and performance science have also begun to adopt AI technologies to gain a competitive advantage over the rest of the field [1]. Given AI's powerful ability to analyze and extract insights from large quantities of data, the first logical step in its implementation must be providing a source of high-quality data - be that by wearable sensors, high-speed video systems or other monitoring devices with the ability to generate continuous streams of physiological, biomechanical, and behavioral data. This analysis, combined with human oversight, is thought to create new opportunities for individualized interventions and decision support in a large variety of settings [2]. In this context, AI could serve as both a computational framework and a practical tool for enhancing performance, preventing injury, and optimizing recovery. One thing that shouldn't be overlooked is the current accessibility of AI models - if they proved to be competent sources of information regarding sport, training and nutrition, it could have beneficial effects on parts of the population not able to afford a personal trainer or isolated in some other ways [3].

The concept of data-driven sports science is not new. Traditional analytics and biomechanical modelling have long contributed to predicting performance, training load management and injury surveillance [4]. However, the rise of machine learning (ML) and deep learning (DL) techniques represents an increase in analytical capability. These systems can learn complex, nonlinear relationships between variables that exceed the capacity of human intuition or conventional statistics [5]. For example, ML algorithms have been applied to predict hamstring injuries, automate movement screening, or optimize team tactics through spatiotemporal player tracking [6]. Similarly, in sports medicine, AI-enhanced diagnostic imaging has demonstrated promise in improving the speed and accuracy of musculoskeletal (MSK) assessments [7].

Despite these advances, the integration of AI into sport and exercise contexts remains limited. Many applications are confined to experimental prototypes and issues of data quality, bias, and model interpretability persist, raising concerns about the transparency and ethical governance of algorithmic systems used in high-stakes performance and clinical decision-making [8]. Furthermore, the balance between automation and human expertise remains a central challenge: while AI can augment decision processes, it should not replace the contextual judgment of clinicians, coaches, or sport scientists.

The present review aims to provide a comprehensive summary of emerging evidence regarding AI applications in sports medicine, performance optimization, and athlete health management. Specifically, it explores two interconnected domains, namely the clinical use of AI in diagnosis, injury prevention, and rehabilitation as well as the application of AI-driven models in performance monitoring, load management and building of a training regimen. By highlighting both opportunities and limitations, this review seeks to support an evidence-based and ethically grounded pathway for AI integration into sport and sport-science practice.

Ultimately, AI's potential to make athletic environments smarter, faster, and safer depends not only on technical innovation but also on interdisciplinary collaboration among engineers, clinicians, sport scientists, and policymakers. Understanding how these technologies reshape decision-making and human performance will be central to realizing their promise while avoiding unintended harm to athlete welfare and integrity.

Background of Artificial Intelligence in Sports

Artificial intelligence (AI) is an umbrella term - it encompasses a broad range of computational methods designed to emulate human cognition and perception. At its core, AI works through algorithms that process large volumes of information and identify relationships between variables to learn from input and past data [9, 10]. Within the context of sports and sport science, AI refers to the use of algorithmic models capable of processing high-dimensional data to recognize patterns, generate predictions, or automate tasks [11]. This section outlines the fundamental principles and modalities of AI, the primary data sources driving its use in sports, and the analytical frameworks through which such systems are deployed.

Core AI Modalities

AI can be categorized into several overlapping modalities, each with unique applications in athletic contexts.

Machine learning (ML) involves algorithms that improve their performance by learning from data, enabling predictive modeling of injury risk, performance outcomes, or physiological responses to training. Supervised learning is widely used for classification and regression problems, such as identifying movement errors from labeled kinematic data. In contrast, unsupervised learning detects hidden structures or clusters in unlabeled data, supporting applications such as athlete profiling or load segmentation. Reinforcement learning (RL), which trains agents to make sequential decisions by maximizing reward signals, is increasingly applied in tactical simulations and adaptive coaching systems [12,13].

Deep learning (DL), a subfield of ML, employs multilayered neural networks capable of processing complex inputs such as video, audio, or sensor data. Convolutional neural networks (CNNs) are particularly effective in computer vision tasks, including pose estimation, movement tracking, and injury mechanism detection from video footage. Recurrent neural networks (RNNs) and their variants are well suited for time-series data from wearables or motion sensors, enabling real-time monitoring of fatigue, stress, or performance trends. More recently, transformer-based architectures have shown promise for multimodal fusion, integrating data streams from diverse sensors or video sources to produce holistic performance insights [12,13].

Natural language processing (NLP) represents another AI domain with emerging utility in sports. NLP enables systems to process and generate human language, supporting automated injury-report extraction from clinical notes, chatbot-based athlete education, and generative AI assistants for coaching and rehabilitation feedback. As large language models (LLMs) such as GPT or BERT variants evolve, their role in knowledge translation and sports data interpretation continues to expand [12,13].

Data Ecosystems in Sports Science

The proliferation of connected devices and digital platforms has transformed the sports data landscape. Key data streams include physiological data (heart rate, heart rate variability, oxygen consumption), biomechanical data (motion capture, force plate outputs, accelerometry), environmental data (temperature, altitude, and playing surface conditions), and behavioral or cognitive data (reaction times, sleep quality, perceived exertion). Increasingly, these datasets are captured through wearable sensors, smart garments and in-field cameras [14].

Integration of these heterogeneous data sources poses analytical challenges but also offers unprecedented opportunities for individualized insights. AI models can identify subtle deviations in movement mechanics or physiological responses before clinical symptoms appear, providing early warnings for overtraining or potential injury. Similarly, multimodal analytics can support dynamic load management by adapting training prescriptions to each athlete's unique recovery profile [15].

2. Research materials and methods

This narrative review aimed to collect and systematize current scientific evidence on the applications of artificial intelligence (AI) in sport performance, sports medicine, and athletes' health. The focus was on how AI supports data-driven decision-making, enhances performance optimization, enables early detection of injury and illness, and contributes to safer and more efficient athlete management.

We conducted a comprehensive review of peer-reviewed literature. The research covered a wide range of sports, including football, baseball, American football, athletics and strength training and involved both elite and recreational athletes.

Common limitations included small sample sizes, limited external validation, lack of transparency in algorithms, and insufficient reporting on fairness or explainability.

3. Description of the state of knowledge

3.1. AI in Sports Medicine and Injury Management

Medicine has been one of the earliest and most visible beneficiaries of artificial intelligence (AI), owing to its reliance on imaging, biomechanics, and large-scale physiological datasets. The convergence of machine learning (ML) and clinical data integration has enabled more precise diagnosis, risk prediction, and individualized rehabilitation strategies. In this domain, AI functions as both a diagnostic adjunct and a decision-support tool, assisting clinicians and physiotherapists in making evidence-informed choices regarding prevention, diagnosis and treatment.

AI-Enhanced Diagnostic Imaging

Diagnostic imaging is a cornerstone of sports medicine - the ability to correlate clinical findings with image studies adds great value to the therapeutic process. Magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound all have their niches in diagnosing injuries, assessing body composition and much more [16]. There is an ever-growing body of evidence showing that AI algorithms provide value in optimizing workflow and augmenting diagnostic performance. Particularly encouraging results can be found in musculoskeletal trauma detection - many studies have been conducted and a lot of them report almost physician-like performance of AI models. Models succeeded in diagnosing fractures of the pelvis, vertebrae, ribs and humerus, among many others [17-20]. One limitation of those algorithms is their high specificity - they often focus on just one bone, or even one particular fragment of a bone. Luckily, there are models being created that show a wider scope of function - Ma et al. reported an accuracy of 90% in detecting and classifying fractures among 20 different bones with a single model [21]. Good performance was also noted in evaluating injuries to ligaments and other soft tissues. AI models have been shown to provide high efficacy in detecting tears in the anterior cruciate ligament and rotator cuff [22,23].

Ultrasound-based assessment has long been considered as a portable and low-cost solution for field-side assessment of injuries [24]. By combining image processing with AI-based classifiers, such systems could possibly assist clinicians in detecting muscle strains, hematomas, and tendon pathologies in real time - lowering the barrier to performing high-quality scans. The issues regarding this approach lie mainly in the subjective manner in which the ultrasonograms are performed as well as high variability of the scan itself [25].

While we should not expect AI models to replace experienced physicians, they can certainly be of help in easing the burden of workload and possibly improving accessibility to high-quality image studies.

Predictive Injury Modelling and Risk Stratification

Another major application of AI in sports medicine lies in injury prediction and prevention. Machine-learning models are capable of identifying complex, nonlinear relationships among biomechanical, physiological, and workload variables that precede injury occurrences

Some successful attempts to predict injuries were made as early as 2020 - for example, a study conducted by Karnuta J. and colleagues, found that machine-learning models predicted future injuries in professional baseball players more accurately than traditional statistical methods [26]. These findings were echoed by Luu et al. in their analysis of NHL player injuries [27]. As one would expect, prior injury history and specific performance measures were key factors in forecasting injury risk. Some researchers focused more on a specific type of injury - Hendrickx et at. studied posterior malleolar fractures exclusively and found success predicting its incidence within a specific group with a machine-learning-based algorithm [28]. In recent years, more studies have emerged, shining light on the matter at hand [29-31]. For example, Tsilimigkras et al. used machine-learning on nine load metric data to predict non-contact muscle injuries in soccer players, successfully identifying risk from workload spikes and cumulative load patterns, and Zhu et al. developed a model combining big-data analytics and neural network based image recognition to predict injury risk in competitive aerobics athletes by identifying soft tissue strain patterns [32,33].

Although predictive models seem to be improving, numerous systematic reviews focused on the topic show that achieving practical generalized utility will be difficult - the general consensus seems to be that more high-quality research is needed [34-37]. The impact of developing software capable of warning teams and players of an increased injury risk is hard to overstate given the amount of money in professional sports [38].

3.2. AI in Performance Science and Training Optimization

It is no secret, that to achieve the level of mastery necessary to succeed where the competition is the fiercest, years of highly specialized training, proper nutrition and adequate recovery are critical [39]. While AI's role in sports medicine primarily focuses on diagnosis and injury prevention, its applications in performance science center on optimizing training, enhancing tactical decision-making, and maximizing athletic output. The combination of large-scale performance data and adaptive machine learning (ML) models has enabled a transition from reactive to predictive and individualized performance management. AI-driven systems can identify subtle performance trends, adapt training programs dynamically, and assist coaches in developing evidence-based strategies that balance load, recovery, and readiness to train or compete.

Load Monitoring and Performance Prediction

Training load management is fundamental to athlete health and performance. Traditionally, coaches have relied on subjective ratings of perceived exertion (RPE), heart rate, and training volume to assess fatigue and readiness [40,41]. AI enhances this process by integrating multimodal datasets - including GPS tracking, accelerometry, biochemical markers, and wellness questionnaires - to detect nonlinear interactions that precede performance decline or injury.

AI models can simulate optimal movement trajectories or mechanical efficiency under varying constraints, informing coaching strategies and rehabilitation protocols. For instance, some studies focused on improving the form of athletes while performing certain exercises - Hu et al. found that using four wearable sensors, they were able to monitor technique and potential injury risk, while Chariar et al. went further, developing a model able to classify seven squat types and provide form-correction suggestions tailored to a user's body proportions [42,43]. Biro et al. investigated a wearable sensor system that used multi-modal data and machine-learning algorithms to continuously monitor activity in real time for early detection of fatigue during physical excercise, potentially aiding in reducing injury risk and optimizing training workload [44]. The integration of biomechanics, physics-based modeling, and AI thus provides a powerful foundation for performance enhancement.

What's more, thanks to advances in AI models we may soon have the ability to simulate the athletes themselves! The concept of 'Digital Twin' refers to a virtual dynamic computational model that continuously mirrors an individual's physiology and biomechanics could find its use in sports science. It would integrate data from sensors and wearables (heart rate, motion capture, workload, recovery metrics) with biomechanical and physiological simulations to forecast performance capacity, injury risk, and rehabilitation progress [45]. Clinicians and coaches could then run "what-if" scenarios-adjusting training loads, nutrition, or therapy parameters - within the twin before applying them in real life [46,47].

In team sports, a Digital Twin could represent the opposing team, providing an opportunity to practice tactical solutions virtually. Team performance is influenced by dynamic, high-dimensional variables such as player positioning, ball movement, and environmental context. Moreover, several studies have attempted to use AI models strategically to better understand team tactics [48,49]. If proven successful, such models could offer a previously unattainable competitive edge, easing the burden of tactical preparation and allowing more time to focus on execution.

Adaptive Coaching and Personalized Feedback

One of AI's most promising contributions to performance science lies in personalized and adaptive feedback systems. Not everyone can afford a personal trainer, but presumably a much larger part of the population would have access to personal training software. Wearable and mobile platforms equipped with embedded AI algorithms can deliver individualized insights into a training regimen. For example, Wu showed that an AI model using deep reinforcement learning can automatically adjust an athlete's training plan to improve performance and recovery [50]. Additionally, Xu et al. showed that a deep reinforcement learning systems can process sensor data in real time to adjust training strategies instantly, allowing faster and more responsive athlete feedback [51]. Similar results were obtained in a simulation run by Connor et al. which showed that an AI-based feedback controller outperformed random and proportional strategies at correcting training plan deviations after disturbances. [52]

The widespread use and easy access to generative AI platforms like GPT or Gemini could make personalized training guidance far more accessible to athletes and recreational users who lack regular access to professional coaching. Havers et al. found that large-language models such as GPT-4 and Google Gemini produced reproducible resistance-training plans when given detailed prompts, although plan quality varied with input specificity [53]. However, a critical evaluation of GPT-4 in exercise prescription found that while the model generated generally safe programs, it frequently lacked the precision, individualization and progression that expert clinicians or coaches provide, and thus cannot yet replace human oversight [54].

Generative AI models and conversational agents are also emerging as educational and motivational tools, capable of delivering tailored feedback and performance summaries, but some studies highlight that more work needs to be done [55,56]. It is worth noting that Barger found that athletes developed equally strong working alliances with AI-based "coaches" as with human coaches, suggesting that automated systems might be accepted as credible partners in training contexts [57].

Athlete Monitoring, Wearables, and Edge AI

Continuous monitoring has become central not only to modern sport science but also to a large portion of the population trying to live a healthier life. The growing availability of wearable devices and biosensors capable of collecting large volumes of physiological data offers unique possibilities, from monitoring cardiac events to optimizing sleep quality - they prove to be helpful both as a medical devices allowing for earlier diagnosis of latent diseases and as a tool for self-betterment [58-60]. Often, even the commercially available wearable devices provide high quality data with limited error rates - it's important to know that data used by models is of high enough quality to be representative of the real world [61].

The use of sensors is even more robust and widespread when considering sport science. Devices such as smartwatches, chest straps, inertial measurement units (IMUs), and smart clothing capture parameters including heart rate, heart rate variability (HRV), accelerometry, skin temperature, sleep quality, and movement kinematics. They offer a perfect, cost-effective solution for monitoring the athlete's performance in more ways than one [62,63]. Artificial intelligence (AI) could play a crucial role in processing these data streams to produce actionable insights on training readiness, recovery, and well-being.

Researchers are working on algorithms able to identify early deviations from an athlete's baseline that may indicate overtraining, illness, or psychological fatigue. Thanks to this, coaches would be able to modify training load and recovery protocols in time to avoid loss of performance or a potential injury [64,65]. Marotta et al. showed that wearable motion sensors can be used to detect signs of fatigue while running, reaching about 76% accuracy with one sensor and up to 90% when several sensors were used [66]. It's easy to see how AI transforming raw sensor output into readable information empowering individualized interventions would have a groundbreaking effect on athlete management. A deeper understanding of fatigue patterns could also help optimize training cycles, allowing athletes to push their limits safely while maximizing performance gains.

As technology continues to advance toward higher levels of intelligent assistance, edge AI and embedded analytics are emerging as key tools for enabling real-time decision-making in both clinical and performance settings. Edge AI refers to artificial intelligence systems that process data directly on a local device such as a smartwatch, sensor, or training computer instead of sending all the information to distant servers [67]. This in turn allows for reduced latency and supports on-device analytics for real-time feedback [68]. By bringing computation closer to the source of data, Edge AI enables faster, more personalized, and privacy-preserving insights that enhance both performance and decision-making in athletic and clinical settings.

Beyond physiology, modern wearables now provide detailed biomechanical insights through accelerometers, gyroscopes, and magnetometers embedded in clothing, shoes, or equipment [69]. AI-based sensor fusion can integrate these signals far more effectively than traditional methods, allowing the reconstruction of motion patterns, estimation of joint angles, and quantification of mechanical load. This, in turn, enables in-field analysis of running gait, jump mechanics, or stroke efficiency without the need for laboratory-based systems [70]. Athletes could receive immediate cues regarding technique adjustments or fatigue-related compensations [71,72]. These instant, data-driven cues enable athletes to correct inefficient movement patterns as they occur, preventing the accumulation of strain that can lead to performance decline or injury over time. In high-performance settings, such responsiveness supports safer and more precise load management.

The combination of continuous sensing and AI-driven interpretation has given rise to adaptive feedback ecosystems that learn from an athlete's ongoing data. Reinforcement learning and adaptive control algorithms can adjust training prescriptions or recovery recommendations automatically, based on evolving physiological states [50]. In practice, such systems might suggest modifying session intensity or rest duration in response to acute fatigue indicators, creating a closed-loop feedback structure between athlete, device, and the coach [73].

Despite rapid adoption, the scientific validation of wearable technologies is inconsistent. Many commercial devices lack peer-reviewed verification of measurement accuracy, reliability, and algorithmic transparency. Device drift, sensor placement variability, and environmental interference can all compromise data quality. Consequently, AI models that depend on these data inherit such limitations. Rigorous validation protocols and open benchmarking datasets are needed to ensure that AI-driven monitoring systems maintain clinical and scientific credibility.

3.3. Data Governance, Ethical Considerations and Evidence Gaps

As artificial intelligence (AI) becomes increasingly integrated into sports medicine, performance science, and athlete monitoring, ethical and governance frameworks have lagged behind technological innovation. The collection, processing, and interpretation of sensitive physiological and behavioral data raise important questions regarding privacy, fairness, transparency, and accountability. Without appropriate oversight, AI systems risk producing unintended harm. Establishing robust data governance is therefore essential to ensure that AI technologies in sport operate within both ethical and legal boundaries [74]. Athlete data is uniquely sensitive, given that it encompasses not only medical records but often also continuous physiological, psychological, and performance-related information. The proliferation of wearables, video systems, and smart training environments has blurred the boundaries between clinical, personal, and competitive data domains. This creates complex challenges for data ownership and informed consent. In many cases, users may lack full understanding of how their data are collected, who controls it, or how it might be used beyond its immediate purpose. Effective data protection requires not only technical safeguards but also organizational and legal mechanisms that define who can access, share, and profit from collected information.

Current Evidence Gaps and Research Directions

Despite the rapid growth of artificial intelligence (AI) applications across sports medicine, performance science, and athlete management, the current evidence base remains fragmented. Most published studies are exploratory, or proof-of-concept investigations conducted in small, homogenous cohorts, with limited external validation. To progress from innovation to reliable clinical and field integration, the scientific community must address several methodological, technical, and ethical gaps. Establishing standardized frameworks for data collection, model validation, and transparent reporting will be essential to ensure reproducibility, generalizability, and responsible adoption of AI in sports and medicine

4. Summary

Introduction and Purpose

Artificial intelligence is reshaping sport by converting continuous, multimodal data into timely, individualized decisions across medicine, performance, and athlete health. This review examines how AI supports practice and decision-making, where it adds value, and what limitations must be addressed to ensure safe, equitable deployment.

Brief Description of the State of Knowledge

Evidence shows that AI can augment diagnostic imaging and clinical triage, surface injury-risk precursors from complex workload and biomechanical signals, and enable adaptive training through closed-loop feedback that operates on the edge—close to the athlete and in real time.

When paired with human oversight, these capabilities promise faster interventions, safer load management, and improved access to high-quality guidance. Nevertheless, model performance is tightly coupled to data quality, which can suffer due to multiple factors. Generalizability is limited by small or homogeneous cohorts, and real-world validation remains rare.

Summary (Conclusions)

The path forward requires scientific rigor and responsible deployment. Priorities include reliable data collection, transparent validation, and close collaboration between scientists, clinicians, and coaches. If developed and used ethically, AI systems—ranging from wearable analytics to digital twins—can shift sport from reactive problem-solving to proactive, personalized care. By ensuring fairness, privacy, and human oversight, these tools can help athletes at every level train smarter, stay healthier, and perform at their best. AI will not replace the art of coaching or clinical expertise, but it can elevate both.

Disclosure

Conceptualization, KMS and KS; methodology, PB and MP; validation, KS, PB, and JZ; formal analysis, MP and FC; investigation, JZ, MK and EK; resources, MK and JB; data curation, PB and FC; writing – original draft preparation, KMS,JZ and EK; writing – review and editing, KS, MP, and JB; supervision, KS; project administration, KMS;

All authors have read and agreed to the published version of the manuscript.

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There is no supplementary material.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

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