REVIEW ARTICLE

Integrating multimodal AI technologies for sports injury prediction and rehabilitation: Systematic review

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ABSTRACT

Traditional methods for sports injury prevention and rehabilitation rely predominantly on subjective clinician-guided assessments and standardized intervention protocols. These approaches often result in limited accuracy, delayed responsiveness, and insufficient personalization. Recent advances in artificial intelligence (AI), wearable sensor technologies, and multimodal analytics provide novel opportunities for objective, real-time, and personalized injury management strategies. Despite these advances, there remains a critical need for systematic synthesis and evaluation of integrated multimodal approaches. This systematic review critically evaluates contemporary developments in multimodal AI technologies applied specifically to sports injury prediction and rehabilitation. We systematically describe the biomechanical and physiological foundations of common acute and chronic sports injuries and present them within an integrated, five-stage injury recovery pipeline. Our analysis emphasizes AI methods including sensor fusion frameworks, time-series classification algorithms, and predictive analytics that enhance early injury detection, accurate risk modelling, and timely interventions. For the rehabilitation phase, we critically assess AI-supported motion quality assessment methods, adaptive feedback mechanisms, and individualized recovery protocols facilitated by wearable and vision-based technologies. Furthermore, we evaluate the real-world deployment and athlete-specific modelling strategies of AI systems, addressing challenges of environmental robustness, computational efficiency, and personalized adaptation. Multimodal AI technologies offer substantial potential for revolutionizing sports injury prediction and rehabilitation by enabling highly individualized, data-driven, and context-aware solutions. Nevertheless, significant challenges persist in the areas of model generalization, interpretability, privacy concerns, and clinical validation. Promising future research directions include the advancement of explainable AI frameworks, digital twin technologies, and multi-agent modelling approaches, aimed at overcoming these limitations and advancing personalized, intelligent sports medicine.
Keywords: Artificial intelligence, Sports injury prediction, Rehabilitation monitoring, Multimodal sensors, Sensor fusion, Predictive analytics, Explainable AI, Personalized feedback, Edge computing.

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INTRODUCTION

Injury prevention and rehabilitation are critical components of modern sports science and athlete management. Sports-related injuries not only compromise athletic performance and career longevity but also impose significant economic and psychological burdens on individuals and institutions. Traditional approaches to injury risk assessment and post-injury rehabilitation often rely on manual observation, subjective clinical judgment, or basic biomechanical evaluations—methods that may lack sensitivity, scalability, and real-time responsiveness (Arzehgar et al., 2025). In recent years, artificial intelligence (AI) has emerged as a promising solution to overcome these limitations by offering data-driven, adaptive, and intelligent support across the full spectrum of injury management (Reis, Alaiti, Vallio, & Hespanhol, 2024; Van Eetvelde, Mendonça, Ley, Seil, & Tischer, 2021).

The proliferation of AI in sports injury science is driven by several factors. First, advances in computer vision, machine learning, and wearable sensor technology have enabled the collection and interpretation of large-scale, multimodal datasets, including kinematic, kinetic, physiological, and environmental information (Cao, Hidalgo, Simon, Wei, & Sheikh, 2021; Picerno, 2017). Second, AI algorithms, particularly those based on deep learning and time-series modelling, have shown the ability to uncover subtle patterns and temporal trends that correlate with increased injury risk or suboptimal recovery trajectories (Hannink et al., 2017; Sadr, Khani, & Tootkaleh, 2025). Third, the emergence of real-time inference platforms and edge AI devices has opened new opportunities for on-field monitoring and closed-loop rehabilitation systems (Sabry, Eltaras, Labda, Alzoubi, & Malluhi, 2022).

This review aims to provide a comprehensive overview of AI-driven approaches for injury prevention and rehabilitation in sports. We structure our discussion around three core pillars of injury management: (1) early prediction and risk modelling, (2) AI-assisted rehabilitation monitoring, and (3) intelligent feedback and personalization. For each area, we analyse representative algorithms, system architectures, and clinical deployment scenarios, with a particular focus on sports-specific datasets, evaluation metrics, and real-world applications.

Furthermore, this review highlights the integration of AI with wearable technologies, such as inertial measurement units (IMUs), electromyography (EMG), and pressure sensors, as well as the rise of digital twin frameworks that simulate and monitor the recovery process (Gu, Lin, He, Zhang, & Zhang, 2023; Hliš, Fister, & Fister Jr, 2024). We also identify key technical challenges—including inter-subject variability, data heterogeneity, model interpretability, and clinical validation—that currently limit the adoption of AI in sports healthcare (Lundberg & Lee, 2017).

By synthesizing current research and projecting future directions, this work intends to serve as a foundational reference for interdisciplinary researchers and practitioners working at the intersection of sports medicine, movement science, rehabilitation engineering, and artificial intelligence. Ultimately, the goal is to facilitate the development of intelligent, personalized, and effective systems for injury prevention and recovery, contributing to safer and more sustainable athletic performance.

OVERVIEW OF SPORTS INJURIES AND RECOVERY PIPELINE

Sports injuries remain a significant concern across all levels of athletic participation, impacting not only physical performance but also psychological well-being and long-term health outcomes. These injuries may occur acutely, as a result of trauma, or develop chronically through repetitive stress and suboptimal biomechanical patterns. As injury rates continue to rise in both amateur and professional sports, there is an urgent need to enhance our understanding of injury mechanisms and optimize the recovery process through data-informed and intelligent solutions. In this context, artificial intelligence (AI) has emerged as a powerful tool for improving injury risk prediction, rehabilitation monitoring, and return-to-sport assessment (Musat et al., 2024).

Common types of sports injuries

Sports-related injuries are generally categorized into two types: acute and chronic. Acute injuries typically result from sudden impact or trauma, leading to conditions such as ligament ruptures—most notably anterior cruciate ligament (ACL) tears—muscle strains, joint dislocations, and bone fractures. These events often require immediate medical attention and structured rehabilitation (B. Y et al., 2025). Chronic injuries, in contrast, develop gradually due to repeated mechanical loading or improper training. Common examples include Achilles tendinopathy, patellofemoral pain syndrome, stress fractures, and overuse-related shoulder or knee issues. These injuries are often harder to detect in early stages and may result in long-term movement impairments if not properly managed (Guo, Liu, & Li, 2024). Understanding these injury types provides the clinical and biomechanical basis for designing AI-supported assessment and intervention tools. AI-driven platforms can leverage diagnostic markers and recovery patterns to inform tailored rehab protocols (Kaur et al., 2020).

Building on our discussion of the clinical and biomechanical underpinnings of sports injuries, Table 1 distils the most prevalent injury types into a structured overview. It aligns each injury—ranging from acute events like ACL ruptures to chronic conditions such as stress fractures—with its characteristic mechanism, hallmark clinical signs, and standard assessment modalities. This consolidated snapshot not only reinforces the five-stage recovery pipeline but also highlights where objective, AI-driven tools can most effectively intervene during early detection and diagnostic evaluation.

Table 1. Key sports injury types and clinical characteristics.

Injury type	Mechanism	Clinical signs	Standard assessment
ACL rupture	Non-contact pivot	Knee instability, pain	Lachman test, MRI
Muscle strain	Overstretch/tear	Localized pain, swelling	Palpation, ultrasound
Patellofemoral pain	Overuse, malalignment	Anterior knee pain	Clinical exam, gait analysis
Stress fracture	Repetitive load	Localized bone tenderness	Bone scan, MRI

This table contrasts common acute and chronic sports injuries by mechanism, hallmark clinical signs, and typical assessment modalities, providing a quick reference for the pipeline stages described in next section.

The sports injury recovery pipeline

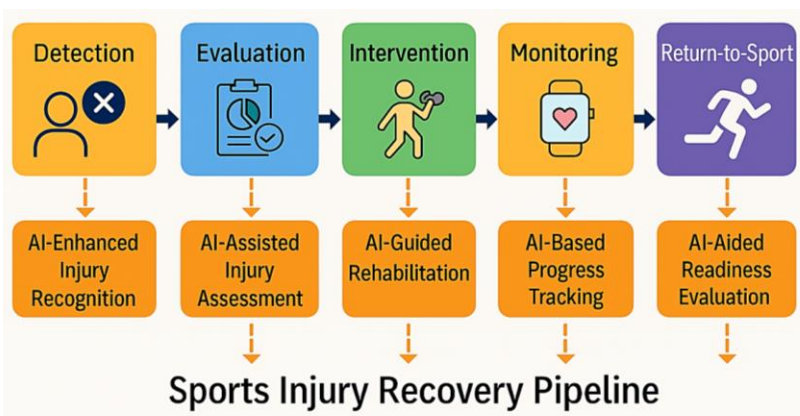
The sports injury recovery process is typically structured as a multi-phase pipeline encompassing detection, evaluation, intervention, monitoring, and reintegration. The first phase involves the recognition and localization of the injury, traditionally based on physical examination, medical imaging, and patient-reported symptoms. In many cases, diagnosis may be delayed or imprecise due to the subjective nature of evaluation. However, AI-assisted diagnostic systems can enhance precision by automatically classifying injury severity based on imaging and motion data (Andriollo et al., 2024). The second phase centres on injury profiling and severity assessment, where clinicians measure range of motion, strength, and movement deficits. AI-based systems are increasingly utilized here to analyse motion asymmetries, segmental imbalances, and sensor-derived patterns that may not be visible to the naked eye (Musat et al., 2024).

Rehabilitation constitutes the third phase and often includes a combination of therapeutic exercises, neuromuscular re-education, and proprioceptive training. AI can play a key role in this stage by providing intelligent feedback on exercise form, dynamically adjusting difficulty levels, and optimizing recovery trajectories based on individual response (Amendolara et al., 2023). The fourth phase introduces continuous monitoring and feedback loops, wherein wearables or computer vision-based systems capture ongoing motion data to prevent compensation patterns and identify signs of reinjury (Ramkumar et al., 2022). Finally, the return-to-sport phase entails decision-making about an athlete's readiness to re-enter competitive environments. Here, AI classifiers trained on longitudinal performance data and risk factors can assist practitioners in making objective and personalized judgments (Yung, Wu, Aus der Fünten, Hecksteden, & Meyer, 2025). Radiomics-based systems have demonstrated over 90% accuracy in predicting time to return-to-play (Desai, 2024).

This pipeline is not strictly linear; instead, it reflects a feedback-rich cycle where monitoring and assessment can trigger earlier re-entry into rehabilitation when necessary. Integrating AI at each stage enables the system to adapt in real time to the athlete's evolving physiological state, thereby improving the efficiency and safety of the recovery process (Leong, Leong, & Leong, 2024).

Limitations of traditional methods

Despite the sophistication of modern sports medicine, traditional approaches to injury prevention and rehabilitation often suffer from critical limitations. Clinical assessments are inherently subjective, with outcomes heavily dependent on practitioner experience and consistency. Data collection is frequently episodic and delayed, reducing opportunities for timely intervention. Moreover, rehabilitation protocols are often designed in a generalized fashion, without accounting for individual differences in anatomy, training history, or responsiveness to therapy (Yung, Ardern, Serpiello, & Robertson, 2022). Finally, real-world applicability is limited, as many existing assessment tools are confined to laboratory or clinical settings and do not translate well to dynamic, on-field environments. These constraints highlight the need for AI-enabled systems that are objective, continuous, and capable of delivering real-time, context-aware insights to both athletes and clinicians (Corban et al., 2021).



Note. The framework illustrates five interconnected stages of recovery, from injury onset to reintegration into sport. Embedded AI components provide predictive modelling, automated assessment, intelligent monitoring, and adaptive feedback throughout the recovery cycle.

Figure 1. The sports injury recovery pipeline and AI integration points.

To visually consolidate the discussion in this section, Figure 1 presents a conceptual flowchart of the sports injury recovery pipeline and highlights the potential roles of AI at each stage. The model reflects a non-linear, feedback-driven process consisting of five key phases: injury detection, evaluation, rehabilitation, monitoring, and return-to-sport assessment. Across this pipeline, AI technologies are embedded to enhance decision-making, personalize recovery trajectories, and enable real-time feedback through sensor analytics, biomechanical modelling, and data-driven planning. This integrated perspective helps contextualize where and how intelligent systems can transform traditional recovery workflows.

AI FOR INJURY RISK PREDICTION AND EARLY DETECTION

Injury risk prediction plays a pivotal role in modern sports science, enabling proactive interventions that reduce injury incidence and improve athlete longevity. Traditional tools such as movement screenings and injury history questionnaires are limited in their predictive power and fail to capture the complex, multifactorial nature of sports injuries. Artificial intelligence (AI) offers a transformative approach, leveraging multimodal data and machine learning models to uncover subtle risk factors and deliver individualized, context-aware assessments (Nechita et al., 2025). This section reviews the primary data sources, modelling techniques, application cases, and challenges associated with AI-based injury prediction in sports.

Multimodal data for risk prediction

A key advantage of AI systems lies in their ability to integrate diverse data streams for comprehensive injury risk assessment. Kinematic and kinetic data, collected through motion capture or wearable inertial sensors, provide detailed information on joint mechanics, asymmetries, and loading patterns—important indicators of musculoskeletal stress (Hudson, Hartigh, Meerhoff, & Atzmueller, 2023). Physiological signals such as heart rate variability (HRV), electromyography (EMG), and muscle oxygenation further reflect fatigue levels and neuromuscular control (Oettl et al., 2025). These data are often supplemented by training loads, recovery logs, sleep metrics, and contextual variables including position played, surface type, or environmental conditions. The integration of such multimodal datasets enhances the robustness and specificity of AI-based risk models (Huang et al., 2022).

Following our examination of multimodal data streams and machine learning architectures for risk modelling, Table 2 clarifies how specific sensor inputs are paired with suitable AI techniques. For example, it shows how IMU kinematic sequences feed into LSTM or Transformer networks to estimate ACL risk (Gai, 2025), while HRV and EMG signals inform SVM-based fatigue indices (W. Li, 2024). By linking each data modality to its typical output metric and a representative sports application, the table makes explicit the end-to-end pathway from raw sensor capture to actionable injury-risk predictions.

Table 2. Data modalities and AI techniques for injury risk modelling.

Modality	AI technique	Typical output	Example use case
IMU kinematics	LSTM, Transformer	ACL risk probability	Running gait analysis
HRV / EMG	SVM, Random Forest	Fatigue index	Overtraining detection
Video (pose)	CNN + GCN	Movement asymmetry score	Jump-landing screening
Training load	XGBoost	Injury likelihood score	Basketball practice load

This table maps key multimodal inputs to the AI algorithms most often used for injury risk prediction, along with their outputs and representative sports applications, complementing the discussion in next section.

Machine learning techniques for injury modelling

A wide range of machine learning algorithms have been applied to injury prediction tasks. Tree-based models (e.g., Random Forest, XGBoost) are popular for their interpretability and performance with structured data

(W. Li, 2024). Support Vector Machines (SVM) are employed in scenarios with high-dimensional but relatively small datasets (Claudino et al., 2019). More recently, neural networks—particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks—have gained traction due to their ability to model temporal dependencies in time-series data such as gait dynamics and fatigue evolution (Adetiba, Iweanya, Popoola, Adetiba, & Menon, 2017). Transformer-based models, known for their self-attention mechanisms, are being explored for long-range motion analysis (Rossi, Pappalardo, & Cintia, 2022). These models are typically trained on retrospective injury datasets and evaluated using classification metrics like accuracy, AUC, sensitivity, and specificity. Class imbalance, a common issue due to the relative rarity of injury events, is addressed through resampling, cost-sensitive training, or synthetic data generation (Zhang, Li, Shao, & Wang, 2024).

Practical applications in sports settings

AI-based risk prediction has been successfully implemented in several sports domains. For instance, IMU-driven models have been used to detect gait asymmetries that correlate with ACL injury risk in runners and jump-based athletes (Calderón-Díaz et al., 2024). In team sports such as soccer or basketball, supervised models trained on training load, perceived exertion, and match exposure have shown potential in forecasting overuse injuries like hamstring strains (Speiser et al., 2021). Increasingly, these systems operate in real time, using wearable sensors and cloud-based inference to provide dynamic risk scores and injury likelihood predictions. These insights are used by coaches, trainers, and medical teams to make informed decisions about workload adjustment, rest periods, and rehabilitation scheduling (Tedesco, Scheurer, Brown, Hennessy, & Flynn, 2022).

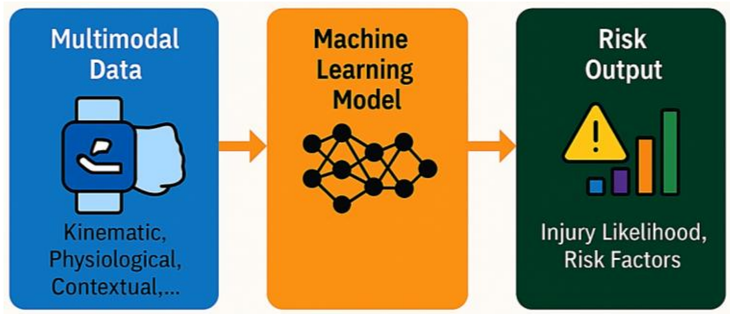
Challenges and limitations

Despite promising developments, several challenges hinder the widespread adoption of AI-based injury prediction systems. Data quality and standardization remain critical bottlenecks, as noise, sensor variability, and inconsistent labelling degrade model performance (Kokkotis et al., 2022). Furthermore, population-specific models may struggle to generalize across sports, age groups, or competition levels (Jauhiainen et al., 2021). A major barrier is the lack of interpretability in deep learning models, which often function as "*black boxes*" and may not provide actionable insights to practitioners. Additionally, issues surrounding data privacy, fairness, and informed consent must be carefully managed, particularly when dealing with sensitive athlete health information.

Toward explainable and personalized prediction

To increase clinical adoption and real-world utility, the future of AI-based injury prediction lies in explainable and personalized systems. Explainable AI (XAI) techniques help interpret model decisions by highlighting influential biomechanical or physiological features, enabling practitioners to understand and trust the output (Mishra, Habal, Garcia, & Garcia, 2024). Personalized modelling, using an athlete's baseline performance and individual characteristics, improves prediction specificity and reduces false positives (Retzepis et al., 2024). Continual learning frameworks—which update model parameters based on ongoing feedback—will further enhance adaptability over time (Sukumar, Zhang, Tao, Wang, & Zhang, 2020). Together, these directions point toward intelligent, athlete-centred systems that actively support injury prevention through early detection and dynamic risk assessment.

To synthesize the key elements discussed in this chapter, Figure 2 illustrates a conceptual pipeline for AI-driven injury risk prediction. The framework begins with multimodal data collection—including motion capture, wearable sensors, physiological measurements, and contextual variables—which serve as input for machine learning algorithms. These models analyse temporal and structural patterns to estimate injury likelihood, ultimately producing real-time risk assessments that can inform training decisions, recovery planning, and medical interventions. This pipeline emphasizes the role of data integration and intelligent modelling in advancing proactive injury prevention strategies.



Note. Multimodal data sources including biomechanical, physiological, and contextual inputs are processed by machine learning models to generate individualized injury risk assessments.

Figure 2. Conceptual pipeline of AI-driven injury risk prediction in sports.

AI-SUPPORTED REHABILITATION MONITORING AND FEEDBACK

Rehabilitation is a critical phase in the sports injury management pipeline, aimed at restoring function, strength, and movement patterns while minimizing the risk of re-injury. Traditional rehabilitation relies heavily on in-clinic supervision and therapist judgment, which can be limited by subjectivity, resource constraints, and lack of real-time feedback. In this context, artificial intelligence (AI) offers transformative potential to enhance rehabilitation precision, scalability, and personalization. By integrating computer vision, sensor analytics, and adaptive modelling, AI systems can support both clinicians and athletes throughout the recovery process—from motion assessment to intelligent feedback and long-term progress tracking.

Intelligent motion assessment and exercise tracking

One of the primary roles of AI in rehabilitation is the automatic evaluation of exercise execution and movement quality. Using video input or data from wearable sensors, AI models—particularly pose estimation and deep learning-based classifiers—can assess joint angles, movement symmetry, and range of motion during rehabilitation exercises (Jubair et al., 2025). Computer vision systems such as OpenPose or BlazePose are increasingly embedded in mobile applications to allow athletes to perform exercises at home while receiving instant feedback on form correctness (Kandala, V, V, & Palaniswamy, 2024). More advanced systems use sequence models (e.g., LSTM or Transformers) to evaluate temporal consistency and to flag irregular patterns that may indicate compensation strategies or improper load distribution (Poongodi, Kavitha, Sathish, & Lakshmana Kumar, 2025).

Real-Time feedback and adaptive support

Beyond passive assessment, AI systems are capable of delivering real-time, actionable feedback to the athlete. Such feedback may be delivered via visual overlays, auditory cues, or haptic signals, alerting the user when an exercise is performed incorrectly or needs adjustment. These capabilities are particularly useful for home-based or remote rehabilitation, where therapist supervision is limited (Khalid et al., 2024). Some systems also adapt the difficulty or number of repetitions in real time based on performance metrics and fatigue signals, mimicking a form of intelligent virtual coaching (Rasa, 2024). Reinforcement learning-based controllers and adaptive feedback loops are being explored to dynamically tune rehabilitation programs in accordance with recovery trajectories (S. C, B. J. J, A. M, V, & A. S, 2024).

Progress monitoring and recovery analytics

AI-enabled platforms can also serve as comprehensive recovery dashboards, continuously tracking progress over time. By aggregating kinematic data, strength metrics, and subjective reports (e.g., pain levels, confidence scores), machine learning algorithms can model the rate of recovery and detect plateaus or regressions (Nicora et al., 2025). Time-series analysis and anomaly detection models can help flag deviations from expected healing curves (Lanotte, O'Brien, & Jayaraman, 2023). These systems assist clinicians in making evidence-based decisions on progressing or modifying rehabilitation plans. Furthermore, recovery profiles can be benchmarked against population-level data or an athlete's pre-injury baseline to provide individualized recommendations.

Applications of wearable and vision-based systems

Several practical implementations of AI-supported rehabilitation have emerged in recent years. Wearable technologies—such as IMU suits, smart garments, and EMG-integrated sensors—enable motion capture and muscle activity tracking outside of lab environments (LaBoone & Marques, 2024). When combined with AI models, these platforms can detect key events such as compensatory strategies or load asymmetry in real-world training contexts (Sumner et al., 2023). On the other hand, vision-based systems using RGB or depth cameras allow for marker less motion analysis, making the technology more accessible for clinics and home use. Hybrid solutions are also being explored, fusing video, audio, and bio signal data for robust, multimodal recovery tracking.

Extending from our survey of AI-enabled assessment and feedback mechanisms in rehabilitation, Table 3 compares four classes of rehabilitation platforms—vision-based, wearable IMU, smart garments, and hybrid solutions. It outlines each system's sensing modalities, feedback channels, real-time capabilities, and deployment contexts. This side-by-side evaluation underscores the trade-offs between immediacy (e.g., haptic cues from wearables) and contextual richness (e.g., combined camera-sensor fusion), guiding readers toward the most appropriate tool for home-based, clinic-based, or elite sports rehabilitation scenarios.

Table 3. Comparison of AI-driven rehabilitation tools.

System type	Sensors	Feedback mode	Real-time?	Deployment context
Vision-based	RGB / depth camera	Visual overlay	Yes	Remote / home rehab
Wearable (IMU)	IMU, sEMG	Haptic, auditory	Yes	Field-based, gym
Smart garments	Strain sensors, pressure	Visual + haptic	Partial	In-clinic, home
Hybrid	IMU + camera + EMG	Multimodal feedback	Yes	Research, elite sport

This table contrasts primary AI rehabilitation platforms, outlining their sensing modalities, feedback channels, real-time capabilities, and deployment contexts, to highlight strengths and limitations discussed in next section.

Limitations and deployment challenges

Despite significant progress, several challenges limit the clinical translation of AI-supported rehabilitation tools. One key issue is model generalization, as AI systems trained on limited or homogeneous datasets may not perform well across diverse populations or injury types (Sardari et al., 2023). Sensor noise, occlusion, and inconsistent lighting can degrade the accuracy of vision-based systems. There are also concerns about data privacy, especially when cloud-based platforms collect sensitive health information. Furthermore, clinicians may be hesitant to rely on "*black-box*" systems without transparent decision-making processes, underscoring the need for interpretable AI and user-centred interface design (Wani, Kumar, Mamta, Bedi, & Rida, 2024).

To visually convey the role of AI in rehabilitation workflows, Figure 3 presents a simplified feedback loop structure. The system begins with continuous motion tracking via cameras or wearable sensors, followed by real-time assessment of movement quality. Intelligent modules provide immediate feedback to the athlete through auditory or visual signals, while adaptive algorithms dynamically adjust exercise difficulty, duration, or form based on individual performance. This closed-loop structure reflects a transition from static rehabilitation protocols to intelligent, responsive systems capable of supporting safe and efficient recovery.

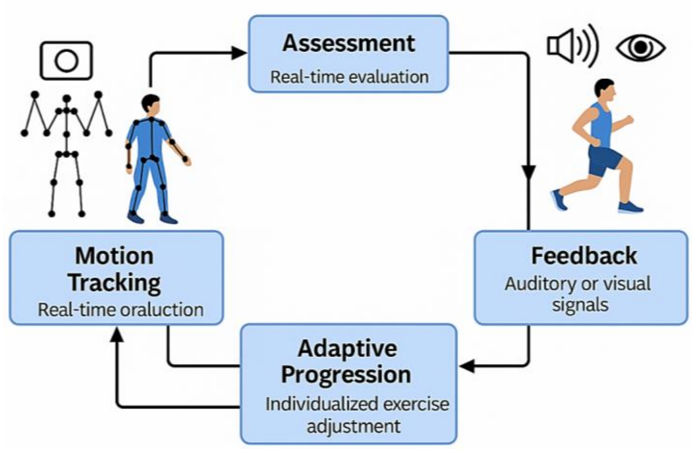


Figure 3. AI-supported rehabilitation feedback loop.

This flowchart illustrates a closed-loop rehabilitation system powered by AI. Motion Tracking (using wearable sensors or vision-based pose estimation) continuously captures exercise movements. Assessment modules then perform real-time evaluation of movement quality and detect compensatory patterns. Based on these insights, Feedback is delivered via auditory, visual, or haptic cues to guide the athlete's form and execution. Finally, an Adaptive Progression engine adjusts exercise difficulty, duration, or repetitions according to performance metrics and fatigue indicators. Arrows denote the continuous exchange of data, enabling dynamic, personalized rehabilitation that adapts as the athlete recovers.

INTEGRATION WITH WEARABLES AND REAL-WORLD DEPLOYMENT

While artificial intelligence (AI) algorithms have demonstrated strong potential in controlled environments, their practical impact in sports injury management critically depends on integration with wearable technologies and deployment in real-world athletic contexts. Bridging this gap requires systems that are not only accurate but also portable, unobtrusive, adaptive, and context-aware. This chapter examines the convergence of AI and wearables, the enabling infrastructure for field-ready deployment, and the key challenges associated with operationalizing such systems in sports environments.

Advances in wearable sensor technologies

Modern wearable systems have evolved far beyond step counters and heart-rate monitors. Current platforms include inertial measurement units (IMUs), surface electromyography (sEMG), pressure-sensing insoles, flexible strain sensors, and smart textiles, capable of capturing rich biomechanical and physiological data in real time. These devices offer a continuous, low-latency stream of data that serves as high-quality input for AI models across risk prediction, rehabilitation monitoring, and feedback generation. For example, multi-sensor garments can detect compensatory gait patterns, asymmetries in joint loading, or improper postural alignments that contribute to injury recurrence (Yadav & Yadav, 2025).

On-device ai and edge computing

To achieve real-time, low-latency feedback in the field, many AI-enhanced systems are being deployed on edge computing devices, such as smartphones, smartwatches, or dedicated AI chips (e.g., NVIDIA Jetson Nano, Apple Neural Engine, Google Edge TPU). These platforms allow motion data to be processed locally, reducing reliance on cloud infrastructure and addressing data privacy concerns. On-device inference also improves system responsiveness, enabling live corrective feedback during rehabilitation exercises or return-to-play assessments. Such architectures are critical for developing mobile, coach-facing, or athlete-facing applications in training centres or on the field (Vijayan, Connolly, Condell, McKelvey, & Gardiner, 2021).

In light of our discussion on integrating AI with wearables and edge computing, Table 4 details the sampling rates, compute requirements, and latency targets for key sensor types—IMUs, sEMG arrays, pressure insoles, and smart textiles—alongside exemplar devices. By specifying microcontroller versus DSP processing needs and acceptable latency thresholds, this table informs the practical design of low-latency, on-device AI inference pipelines that are robust enough for deployment in dynamic, real-world athletic environments.

Table 4. Wearable sensors and edge-AI deployment requirements.

Sensor type	Sampling rate	Compute needs	Latency target	Example device
IMU	100–400 Hz	Low (microcontroller)	< 50 ms	Xsens MVN Link
sEMG	500–2000 Hz	Medium (DSP/CPU)	< 100 ms	Myo armband
Pressure insole	100 Hz	Low	< 100 ms	Loadsol (Novel)
Smart textile	50–100 Hz	Low–Medium	< 200 ms	Hexoskin smart shirt

This table outlines key wearable technologies, their sampling characteristics, and on-device processing requirements, directly informing the edge-AI and deployment considerations in next section.

Contextual adaptation and environmental robustness

Real-world deployment introduces variability in surface type, lighting, noise, clothing, and environmental conditions that challenge AI models trained in controlled laboratory settings. Systems must be designed to operate reliably in unstructured, dynamic environments—such as outdoor tracks, gyms, or sports arenas—where occlusions, perspiration, and hardware misalignment are common. Robust data preprocessing, adaptive filtering, and sensor fusion techniques (e.g., combining IMU + vision + EMG) improve performance under such conditions (Babu, Thuau, & Mandal, 2023). Additionally, self-calibration and context-aware models are being explored to automatically adapt AI behaviour to new users or surroundings.

Athlete-specific modelling and personalization

Wearable-AI systems also enable personalized modelling, where each athlete's unique movement patterns, anatomical characteristics, and injury history are embedded into the system's prediction and recommendation pipeline. Longitudinal data collected via wearables can be used to build individualized baselines and track deviations across training cycles. For instance, a smart insole might detect early changes in plantar pressure distribution indicative of overload, triggering a tailored intervention before injury onset. This aligns with the broader movement toward precision sports medicine, where interventions are dynamically adapted to the athlete's state and context (Seçkin, Ateş, & Seçkin, 2023).

Data infrastructure, privacy, and deployment challenges

Despite technological readiness, large-scale adoption of AI-wearable systems still faces data governance and operational challenges. Reliable performance requires secure pipelines for data acquisition, annotation, storage, and transmission, as well as mechanisms for privacy protection and ethical compliance. Deployment across teams and institutions introduces issues of interoperability, battery efficiency, and cost scalability. Moreover, acceptance by coaches, clinicians, and athletes is contingent on usability, transparency, and demonstrable value in improving performance or reducing injury burden (A. Li & Huang, 2024). Future work must emphasize user-centred design and clinically validated outcomes to facilitate trust and uptake.

By uniting advanced wearable sensors, on-device AI inference, context-aware adaptation, and secure, personalized modelling, next-generation platforms overcome traditional laboratory constraints and deliver continuous, actionable insights directly in the field. Figure 4 summarizes this end-to-end system: raw data from IMUs, sEMG arrays, pressure insoles, and smart textiles are processed on edge devices (e.g., smartphones, AI accelerators) for low-latency feedback, while environmental adaptation modules ensure robustness under changing conditions. Concurrently, cloud-backed, privacy-preserving pipelines refine athlete-specific baselines for risk prediction and rehabilitation progress, closing the loop with real-time, multimodal cues that guide training adjustments and recovery interventions on the pitch, court, or track.

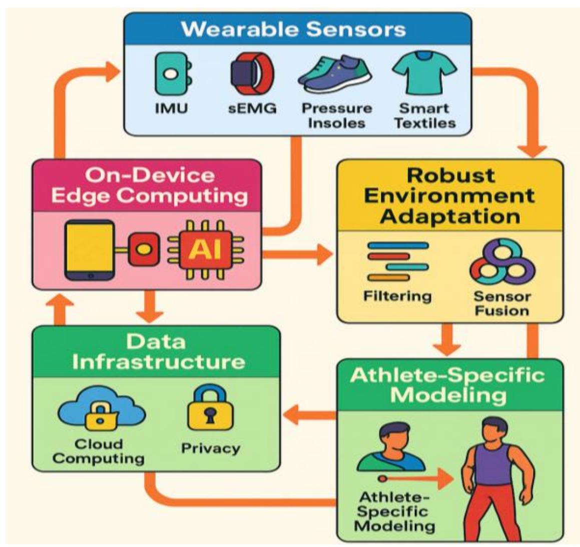


Figure 4. Integration of AI and wearables for real-world sports deployment.

Wearable sensors—including IMUs, sEMG arrays, pressure-sensing insoles, and smart textiles—continuously stream biomechanical and physiological data to on-device edge computing platforms (e.g., smartphones, dedicated AI chips). Robust environmental adaptation modules apply adaptive filtering and multi-sensor fusion to ensure reliable performance across variable lighting, surfaces, and user postures. Athlete-specific modelling components leverage secure cloud infrastructures and privacy-preserving techniques to establish personalized baselines for risk prediction and rehabilitation guidance. Continuous feedback loops deliver real-time, context-aware insights—via visual, auditory, or haptic cues—directly to athletes and coaches in training and field settings, enabling proactive injury management and tailored recovery interventions.

CONCLUSION

Artificial intelligence (AI) is transforming the landscape of sports injury prevention and rehabilitation by introducing intelligent, data-driven solutions that surpass the limitations of traditional assessment and intervention methods. By integrating multimodal sensor data, advanced machine learning algorithms, and real-time processing capabilities, AI-enabled systems offer unprecedented opportunities for early injury risk detection, precise rehabilitation monitoring, and personalized feedback across diverse athletic populations.

This review has provided a comprehensive synthesis of recent advances across the AI-injury management pipeline. In injury risk prediction, machine learning models have demonstrated the ability to identify subtle biomechanical and physiological precursors to injury, especially when trained on high-quality, longitudinal datasets. In the rehabilitation domain, AI-supported systems are enhancing motion quality analysis, delivering real-time feedback, and adapting interventions dynamically based on user-specific recovery trajectories. Furthermore, the integration of wearable technologies and edge computing infrastructures has enabled the deployment of AI systems outside controlled laboratory environments, bringing intelligent feedback directly into training fields, clinics, and homes.

Despite these advances, challenges remain. Model generalization, interpretability, data privacy, and clinical acceptance continue to limit widespread adoption. Many systems still lack standardization in data collection, validation protocols, and usability design. Additionally, the absence of large-scale, domain-specific benchmark datasets hinders the fair evaluation and comparison of emerging methods. Addressing these challenges will require interdisciplinary collaboration among AI researchers, sports scientists, clinicians, and hardware developers.

Looking forward, the field is poised to shift toward personalized, explainable, and context-aware AI systems that adapt to individual athlete profiles and environmental conditions. The integration of digital twin frameworks, multi-agent behaviour modelling, and multi-modal interfaces promises to expand the functional scope of AI in sports medicine. With continued progress in sensor technology, learning algorithms, and ethical governance, AI is expected to become a core enabler of injury-resilient training, optimized performance, and long-term athlete health.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication. P.W wrote the entire manuscript, S.W reviewed the manuscript and made corrections, and P.W and A.W processed the tables and figures.

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DISCLOSURE STATEMENT

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