Artificial Intelligence in Sports Injury Prediction, Diagnosis, and Rehabilitation: An Integrative Review of Multimodal Approaches, Risk Factor Identification, and Clinical Implications

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***Abstract*—Sports injuries represent a significant global health burden affecting athletes at all levels of competition, with profound implications for performance, career longevity, psychological wellbeing, and healthcare costs. Traditional approaches to sports injury management relying primarily on manual clinical assessment, subjective observation, and standardized intervention protocols are inherently limited in their accuracy, scalability, and capacity for personalization. This integrative review synthesizes findings from three contemporary publications to comprehensively examine the current state, methodological diversity, and clinical implications of artificial intelligence (AI) applied to sports injury prediction, diagnosis, and rehabilitation. The review evaluates both classical machine learning and advanced deep learning frameworks, multimodal sensor integration, explainable AI techniques, and real-world deployment strategies. Three source documents were reviewed: (1) an original research article proposing the Biomechanically Informed Neural Network (BINN) and Adaptive Sports Medicine Strategy (ASMS) frameworks; (2) a systematic review of multimodal AI technologies for sports injury prediction and rehabilitation; and (3) a scoping review mapping AI - based identification of conventional and unconventional risk factors for sports injuries across 59 studies. Findings were synthesized narratively across key themes including data modalities, algorithmic approaches, clinical outcomes, and deployment challenges. AI driven frameworks demonstrate consistent superiority over traditional approaches across multiple performance metrics. The proposed BINN+ASMS model achieved an AUC of 0.912 on musculoskeletal radiograph datasets and 0.902 on sports specific injury data, with strong clinical correlation scores confirmed by domain experts. Across 59 studies in the scoping review, tree-based ensemble methods (25.4%) and support vector machines (15.3%) dominated the landscape, with deep learning approaches increasingly applied to temporal and image-based data. Multi modal sensor integration combining kinematic, physiological, and contextual data emerged as a consistent predictor of improved model performance. Unconventional risk factors including sleep quality, psychological stress, and accumulated fatigue were increasingly incorporated alongside conventional biomechanical predictors. AI technologies hold transformative potential for sports medicine through enhanced injury risk prediction, personalized rehabilitation, and real-time monitoring. However, significant challenges remain in model generalizability, external validation, interpretability, data privacy, and clinical integration. Future progress will require multicenter prospective studies, standardized reporting frameworks, and deliberate translation of AI outputs into athlete care pathways.**

***Index Terms*—Artificial Intelligence, Sports Injury, Biomechanical Analysis, Machine Learning, Deep Learning, Wearable Sensors, Multimodal Data Fusion, Rehabilitation Optimization, Explainable AI, Injury Risk Prediction, BINN, ASMS, Edge Computing, Personalized Medicine.**

I. INTRODUCTION

Sports injuries represent one of the most pervasive and costly health challenges in both professional and recreational athletic communities. From acute traumatic events such as anterior cruciate ligament (ACL) ruptures and muscle tears to chronic overuse conditions such as tendinopathy, stress fractures, and patellofemoral pain syndrome, these injuries impose substantial burdens at individual, institutional, and societal levels. Beyond their immediate physical consequences, sports injuries compromise career longevity, psychological wellbeing, and economic productivity, making effective prevention and management a central priority in modern sports science and medicine [1,2].

Historically, the assessment of injury risk and the planning of rehabilitation have depended on practitioner experience, manual observation, and standardized clinical tests. While these approaches carry inherent expertise driven value, they are limited by subjectivity, episodic data collection, and an inability to integrate the complex, multidimensional nature of injury risk in real time. The identification of risk factors has traditionally focused on prior injury history, training load, age, and anthropometric characteristics important variables, but insufficient alone to capture the full spectrum of biological, psychological, and environmental contributors to injury susceptibility [3].

The emergence and rapid maturation of artificial intelligence (AI) in healthcare have opened a new paradigm for sports medicine. AI-driven systems encompassing classical machine learning algorithms, deep neural networks, computer vision, and timeseries modelling offer the capacity to process large, heterogeneous datasets and uncover subtle patterns that elude conventional analysis. These capabilities are increasingly being harnessed to predict injury risk before it manifests, monitor athlete health and rehabilitation in real time, and tailor intervention strategies to individual physiological and biomechanical profiles [4,5].

Simultaneously, the proliferation of wearable sensor technologies including inertial measurement units (IMUs), surface electromyography (sEMG), GPS trackers, and pressure sensing insoles has enabled continuous, ecologically valid data collection across training and competition environments. When paired with AI models, these technologies create a closed loop system capable of transforming raw biomechanical and physiological signals into actionable clinical insights [6].

This integrative review synthesizes findings from three contemporary sources representing distinct but complementary contributions to the field: an original methodological study proposing the Biomechanically Informed Neural Network (BINN) and the Adaptive Sports Medicine Strategy (ASMS) [7]; a systematic review evaluating multimodal AI technologies across the injury management pipeline [8]; and a scoping review mapping the landscape of AI -based risk factor identification across 59 empirical studies [9]. Together, these sources provide a comprehensive and Mult perspective account of the current state and future trajectory of AI in sports injury science. The objectives of this review are: (1) to synthesize the algorithmic approaches and data modalities employed in AI -based sports injury research; (2) to evaluate the clinical performance and translational relevance of proposed frameworks; (3) to identify persistent gaps in model generalizability, interpretability, and clinical deployment; and (4) to propose directions for future research that bridge methodological innovation and real-world impact.

II. BACKGROUND AND EPIDEMIOLOGY OF SPORTS INJURIES

A. Classification and Mechanisms of Injury

Sports related injuries are broadly categorized as acute or chronic. Acute injuries arise from sudden mechanical forces and include ligament ruptures most notably ACL injuries bone fractures, muscle tears, and joint dislocations. These events frequently require immediate medical attention and structured rehabilitation periods lasting weeks to months. Chronic injuries, in contrast, develop insidiously through repetitive mechanical loading and suboptimal biomechanical patterns, manifesting as Achilles tendinopathy, overuse related shoulder pathologies, stress fractures, and iliotibial band syndrome [8].

Understanding injury mechanisms at a biomechanical level is foundational to AI-based prediction systems. Joint angles, ground reaction forces, muscle activation patterns, and gait symmetry indices all serve as quantifiable proxies for injury risk and inform the feature engineering strategies of predictive models. For instance, abnormal knee valgus angles during landing tasks have been consistently associated with ACL injury risk, while asymmetric muscle activation patterns in the lower extremity predict hamstring strain susceptibility [9].

B. The Limits of Traditional Assessment

Despite decades of biomechanical and epidemiological research, traditional injury prevention and rehabilitation methods continue to face fundamental constraints. Clinical assessments are timebound and cross-sectional, providing only a snapshot of an athlete's physiological state rather than capturing the dynamic trajectories that precede injury. Rehabilitation protocols are often developed using population level evidence but applied without systematic adjustment to individual anatomical, training, or psychological variables [8]. Moreover, the reliance on episodic clinical encounters means that early warning signals micro changes in movement quality, rising fatigue markers, or deteriorating sleep metrics frequently go undetected until injury has already occurred. The failure to integrate unconventional risk factors such as psychological stress, sleep quality, and accumulated fatigue into standard care pathways represents a significant gap that AI systems are increasingly equipped to address [9].

III. ARTIFICIAL INTELLIGENCE METHODS IN SPORTS INJURY RESEARCH

A. Machine Learning Approaches

Classical machine learning algorithms have formed the cornerstone of AI-based sports injury research. Across the 59 studies reviewed in the scoping analysis, tree-based ensemble methods particularly Random Forest and Gradient Boosting (XGBoost) were the most frequently applied approaches, accounting for 25.4% of all techniques, valued for their interpretability and strong performance with structured, tabular data [9]. Support Vector Machines (SVMs) represented the second most common technique (15.3%), often applied to high dimensional biomechanical and workload datasets. Logistic regression, KNearest Neighbors, and Naive Bayes were used in exploratory predictive modelling contexts. Recurrent Neural Networks (RNNs) and Long Short-term Memory (LSTM) networks have gained particular prominence for modelling temporal dependencies in timeseries data such as gait dynamics, training load progressions, and physiological fatigue indicators. Transformer-based architectures, leveraging self-attention mechanisms, are increasingly being explored for long-range motion pattern analysis, an area where traditional recurrent models face limitations in capturing distant temporal relationships [8].

B. Deep Learning for Medical Imaging

Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in sports injury diagnosis through automated analysis of MRI, CT, and ultrasound images. Architectures including ResNet50, Dense Net, U-Net, and Mask RCNN have demonstrated high accuracy in detecting ACL tears, rotator cuff injuries, cartilage degeneration, and stress fractures in some cases matching the diagnostic performance of experienced radiologists [7]. The proposed BINN framework by Ma Yin (2025) extends this paradigm by integrating vision guided and text guided samplers to extract multimodal representations from both imaging and kinematic data. The framework achieved an accuracy of 94.67% on the CamVid dataset and an AUC of 0.912 on the MURA musculoskeletal radiograph dataset outperforming established baselines including Mask RCNN (AUC: 0.895) and DeepLabV3 (AUC: 0.888) [7].

C. Biomechanically Informed Neural Network (BINN)

BINN represents a significant conceptual advance over generic deep learning architectures by embedding domain specific biomechanical knowledge into the network's design. Rather than treating the prediction task as a blackbox regression problem, BINN incorporates priors related to joint coordination, temporal symmetry, and gait regularity as structural constraints on the learned representations [7]. The architecture processes kinematic and kinetic data through convolutional layers to extract spatial movement features, then applies a Bidirectional LSTM (BiLSTM) to capture long-range temporal dependencies across movement sequences. A self-attention mechanism further refines feature selection by dynamically amplifying clinically relevant signals such as joint angle asymmetries and abnormal cardiovascular markers while suppressing noise. SHAP (SHapley Additive Explanations) analysis confirmed that joint angle deviations and motion symmetry indices were the most influential predictors of injury risk classification, validating the model's biomechanical alignment [7].

D. Adaptive Sports Medicine Strategy (ASMS)

Complementing BINN, the Adaptive Sports Medicine Strategy operates as a dynamic decision-making framework that continuously updates injury risk assessments and rehabilitation protocols based on real-

time multimodal data. ASMS integrates a feedback driven learning mechanism that minimizes prediction errors over time through gradient descent optimization, allowing the system to adapt to evolving athlete physiological states [7].
The personalized intervention optimization module formulates rehabilitation planning as a constrained optimization problem, balancing risk reduction against performance maximization within specified training load constraints. This mathematical formalization enables ASMS to move beyond one size fits all protocols toward genuinely individualized care a significant step toward precision sports medicine [7].

IV. MULTIMODAL DATA INTEGRATION AND SENSOR TECHNOLOGIES

A defining feature of state of the art sports injury AI systems is their capacity to integrate diverse, heterogeneous data streams. Kinematic and kinetic variables including joint angles, ground reaction forces, acceleration profiles, and counterpressure trajectories provide foundational biomechanical information. Physiological monitoring data, encompassing heart rate variability (HRV), electromyography (EMG), oxygen saturation, and respiratory rate, offers insight into internal load and neuromuscular fatigue. Training load metrics, recovery scores, sleep data, and psychological assessments further enrich the predictive feature space [8,9].
The integration of these modalities has been shown to substantially improve prediction specificity and sensitivity compared to single modality models. For example, combining MRI evidence of early cartilage degeneration with gait analysis data revealing abnormal load distribution creates a richer, more actionable injury risk profile than either source alone. The scoping review found that 86.3% of included studies relied on combinations of multiple sensors and data sources, underscoring the field's shift toward holistic, multimodal assessment [9].

A. Wearable Sensor Technologies

Modern wearable systems extend far beyond consumer fitness trackers, encompassing IMU-based motion capture suits, sEMG arrays, pressure sensing insoles, flexible strain gauges, and smart textiles. These devices offer low latency, continuous biomechanical and physiological data capture in ecologically valid field settings circumventing the constraints of laboratory-based measurement. Among the most frequently used devices in reviewed studies were force plates and dynamometers (10 studies), camera -based systems (8 studies), GPS/GNSS trackers (7 studies), and smartwatch type wearables (7 studies) [9].
Edge computing architectures processing AI inference locally on devices such as smartphones, dedicated AI accelerators (e.g., Apple Neural Engine, NVIDIA Jetson Nano), or embedded microcontrollers enable real-time feedback delivery with sub50ms latency, critical for on field applications where cloud connectivity may be unavailable or insufficient [8].

V. RISK FACTOR IDENTIFICATION: CONVENTIONAL AND UNCONVENTIONAL

The scoping review by Martinez Mora and colleagues identified a rich and expanding landscape of AI modelled injury predictors. Conventional risk factors prior injury history, training load spikes, age, sex, and joint biomechanics remained the most frequently modelled variables and demonstrated consistent associations across sports and algorithms. Knee injuries, particularly ACL pathology, were the most studied outcomes, with graft rupture risk associated with knee hyperextension (70%), medial meniscectomy (20%), and time to return to sport [9].
However, a growing body of evidence highlights the predictive value of unconventional factors. Sleep quality metrics, psychological stress indicators, and accumulated fatigue derived from wearable sensors emerged as increasingly incorporated predictors in recent studies, reflecting broader recognition of the multidimensional nature of injury susceptibility. The study by Iatropoulos et al. (2025), cited in the scoping review, demonstrated that integrating sleep and psychological state into machine learning models for athletic injury forecasting improved predictive accuracy beyond conventional load-based models alone [9].
This shift toward holistic risk profiling aligns with the integrative approach of BINN and ASMS, which explicitly fuse physiological, biomechanical, and performance related data streams into a unified predictive architecture. SHAP analysis within the BINN framework confirmed that physiological signals

including heart rate variability and EMG activation contributed substantially to injury risk predictions, particularly in scenarios characterized by fatigue [7].

VI. AI SUPPORTED REHABILITATION AND RETURNTOSPORT

Rehabilitation represents the phase of injury management where AI has perhaps the most immediate clinical potential given the complexity and individual variability of recovery trajectories. Traditional rehabilitation relies on scheduled in clinic assessments and therapist judgment methods that are temporally coarse and subject to interrater variability. AI supported systems offer continuous, objective monitoring of movement quality, exercise execution, and recovery progression [8]. Computer vision platforms incorporating pose estimation algorithms (e.g., OpenPose, BlazePose) and mobile applications allow athletes to perform exercises at home while receiving automated feedback on joint angles, movement symmetry, and repetition quality. Sequence models, including LSTM and Transformer architectures, evaluate temporal consistency across exercise sessions and flag compensation patterns or load asymmetries that may signal reinjury risk [8].
Reinforcement learning -based adaptive controllers are emerging as a particularly promising approach for dynamically tailoring rehabilitation difficulty and intervention timing -based on athlete specific performance trajectories. These systems effectively implement intelligent virtual coaching adjusting protocols in real time rather than on fixed weekly schedules bringing rehabilitation closer to the individualized model that clinical evidence supports but resource constraints often prevent [8]. Return to sport decision making has traditionally been one of the most challenging and consequential judgments in sports medicine, with premature return frequently resulting in reinjury and delayed return contributing to deconditioning and psychological burden. AI classifiers trained on longitudinal performance data, functional test outcomes, and imaging biomarkers have demonstrated over 90% accuracy in predicting time to return to play in some contexts, offering data driven support for these high stake's decisions [8].

VII. EXPLAINABILITY, CLINICAL INTEGRATION, AND ETHICAL CONSIDERATIONS

A. Explainable AI in Sports Medicine

A persistent barrier to the clinical adoption of AI models is their opacity the tendency of complex neural network architectures to function as 'black boxes' whose decision-making processes are opaque to the practitioners relying on their outputs. This limitation is particularly consequential in clinical settings where understanding the rationale behind a prediction is essential for informed decision-making and professional accountability [8].
Explainable AI (XAI) techniques including SHAP, Gradient weighted Class Activation Mapping (GradCAM), and attention weight visualization provide mechanisms for making model predictions interpretable without sacrificing predictive performance. In the BINN framework, SHAP analysis revealed that joint angle deviations and motion symmetry indices were the strongest contributors to injury risk classification, providing clinically meaningful insights that align with established biomechanical understanding and can support practitioner trust in the model's outputs [7].

B. Clinical Integration Pathways

For AI models to achieve meaningful clinical impact, they must be embedded within existing healthcare workflows rather than positioned as standalone tools. Electronic health record (EHR) integration, athlete management system compatibility, and user centered interface design are prerequisite conditions for widespread adoption. AI outputs must be presented in formats accessible to clinicians without machine learning expertise as actionable risk scores, visual dashboards, and plain language recommendations rather than raw probabilistic outputs [8,9]. The validation of AI models on independent, prospectively collected datasets across diverse athletic populations remains a critical unmet need. Many existing models are trained and evaluated on single institution or single sport datasets, raising legitimate concerns about generalizability. Multicenter prospective cohort studies, incorporating standardized injury surveillance frameworks aligned with International Olympic Committee consensus guidelines, are essential prerequisites for clinical deployment [9].

C. Ethical and Privacy Considerations

The collection of continuous biometric, physiological, and performance data introduces significant ethical considerations around data ownership, privacy, informed consent, and potential misuse. Athletes must be fully informed about what data are collected, how they are processed, with whom they are shared, and how long they are retained. Federated learning architectures which train models across distributed datasets without centralizing raw data represent a technically promising approach to preserving privacy while enabling model improvement at scale [7,8].

Algorithmic bias poses an additional concern: models trained predominantly on data from elite adult male athletes in high income countries may perform poorly when applied to youth athletes, female athletes, or populations in low resource settings. Deliberate attention to demographic diversity in training datasets, and systematic evaluation of model performance across subgroups, is necessary to ensure equitable benefit from AI-based sports medicine [9].

VIII. FUTURE SCOPE AND RESEARCH DIRECTIONS

A. Digital Twin Technologies

Among the most promising emerging paradigms is the development of athlete specific digital twins' computational models that continuously update to reflect an individual athlete's physiological state, movement patterns, and injury history. By simulating the athlete's response to proposed training stimuli or rehabilitation interventions before they are implemented, digital twins could enable proactive, truly personalized sports medicine. Integration with multimodal sensor streams and AI prediction engines would allow digital twins to serve as real-time decision support tools for coaches, clinicians, and athletes alike [8].

B. Foundation Models and Large Language Models

The application of largescale foundation models pre trained on vast, diverse medical and biomechanical datasets to sports injury contexts represents a potentially transformative direction. Such models could enable rapid adaptation to new sports, injury types, or athlete populations with minimal task specific training data, addressing one of the most persistent limitations of current AI systems. The integration of large language models (LLMs) for synthesizing clinical notes, athlete questionnaires, and sensor data into unified risk profiles is an area of nascent but accelerating interest [9].

C. Multi Agent and Federated Learning Systems

Multiagent AI architectures, in which distinct models specialize in different aspects of athlete monitoring (e.g., injury risk, fatigue management, performance optimization, mental health), and exchange information through structured communication protocols, offer a scalable approach to the complexity of comprehensive athlete management. Federated learning frameworks enable these architectures to improve collaboratively across teams and institutions without compromising data privacy a particularly important consideration for team sports organizations where competitive sensitivity is a concern [8].

D. Standardization and Benchmarking

Progress in AI-based sports injury research is currently hampered by heterogeneity in data collection protocols, injury definitions, model architectures, and reporting standards. The establishment of sport specific benchmark datasets curated with standardized injury surveillance methodologies, multi sensor data collection protocols, and demographic documentation would enable meaningful comparison of competing approaches and accelerate identification of best practices. Open model sharing and preregistration of validation studies would further enhance reproducibility and scientific rigor [9].

E. Longitudinal and Prospective Study Designs

The preponderance of retrospective study designs in the current literature limits the causal inference necessary for robust injury prevention guidance. Prospective multi center cohort studies which follow athletes across full competitive seasons while continuously collecting multi modal sensor and clinical data are essential for validating predictive models in real world conditions, assessing their impact on injury incidence when integrated into athlete care pathways, and capturing the temporal dynamics of risk factor accumulation [9].

F. Personalized Medicine and Precision Rehabilitation

The ultimate vision of AI in sports medicine is a precision model of care in which every prediction, intervention, and monitoring protocol is individualized to the specific athlete's biology, biomechanics, psychology, and competitive context. Achieving this vision will require not only technical advances in AI including continual learning systems that update in response to individual feedback but also organizational and cultural changes in how sports medicine teams collect, share, and act on data. The integration of genomic, epigenetic, and microbiome data alongside traditional biomechanical and physiological variables may further enrich predictive models and enable interventions targeting root biological mechanisms of injury susceptibility [7,8].

IX. CONCLUSION

This integrative review confirms that artificial intelligence has matured into a legitimate and clinically meaningful tool for sports injury prediction, diagnosis, and rehabilitation. Across the three source documents reviewed, a consistent picture emerges: AI systems that integrate multi modal data combining kinematic, physiological, imaging, and contextual information consistently outperform traditional diagnostic and predictive approaches on validated clinical metrics. The BINN and ASMS frameworks demonstrate that embedding biomechanical domain knowledge into neural network architectures enhances both predictive accuracy and clinical interpretability. The systematic and scoping reviews confirm the field's rapid growth, particularly in classical machine learning applied to structured sensor data, while identifying persistent challenges in external validation, model transparency, and clinical translation.

The path forward requires a coordinated effort spanning AI research, sports science, clinical medicine, and regulatory governance. Multi center prospective studies with standardized data collection and reporting, deliberate attention to demographic diversity, and meaningful engagement with athletes, clinicians, and ethicists are all necessary conditions for realizing the full potential of AI-driven sports medicine. With these foundations in place, AI systems hold genuine promise to reduce the incidence and severity of sports injuries, accelerate rehabilitation, and support athletes toward safer and more sustainable performance.

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