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Artificial Intelligence Driven Wearable Sensor Data Sports Injury Risk Prediction Athletes: A Systematic Review

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Abstract

Sports injury risk prediction using wearable sensor data and artificial intelligence has become increasingly relevant in athlete monitoring, yet the available evidence remains fragmented across sensor modalities, machine learning models, injury definitions, validation strategies, and implementation contexts. This study aimed to synthesize current evidence on artificial intelligence-driven wearable sensor data for sports injury risk prediction among athletes and to develop an integrative evaluation framework. A systematic literature review was conducted using Scopus as the main database, guided by the PRISMA flow and the PIOS framework. The initial search identified 136 records; all records were screened based on title, abstract, and metadata; 31 reports were assessed for eligibility; and 29 studies were included in the main extraction matrix. The data were analyzed using thematic synthesis with a narrative-integrative approach. The synthesis showed that injury risk was operationalized through biomechanical indicators, neuromuscular activation, physiological fatigue, movement quality, and training-load exposure. The dominant technologies included inertial measurement units, accelerometers, global positioning systems, electromyography sensors, wearable insoles, stretch sensors, heart-rate-related devices, and multimodal sensor systems. The applied models included logistic regression, random forest, support vector machine, XGBoost, long short-term memory, Transformer, temporal convolutional network–Transformer, spatial-temporal graph convolutional network, and multimodal fusion models. This review concludes that artificial intelligence and wearable sensor-based injury prediction should be evaluated as an integrated system connecting sensors, features, models, outcomes, validation, and implementation readiness.

Keywords: Artificial intelligence; wearable sensor; sports injury prediction; machine learning; athlete monitoring.

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INTRODUCTION

Sports injury risk prediction has become an increasingly important area of inquiry in athlete monitoring, sports medicine, biomechanics, and performance science because injury prevention requires timely, context-sensitive, and evidence-informed interpretation of athlete data. Recent literature indicates that wearable sensor technologies and artificial intelligence-based analytical approaches are being used to capture and interpret multiple dimensions of athlete risk, including biomechanical loading, neuromuscular activation, movement quality, physiological fatigue, training-load exposure, and sport-specific risk indicators. The reviewed studies show that wearable systems such as IMUs, accelerometers, GPS devices, EMG/sEMG sensors, insole pressure sensors, stretch sensors, heart-rate monitors, and flexible sensors have been applied across diverse sport contexts to generate sensor-derived features for injury risk prediction or injury-related monitoring. For example, studies have used IMUs and sEMG to classify ACL and muscle-strain risks, EMG features to examine landing-related injury-risk indicators, wearable insoles to estimate lower-limb load, GPS-derived metrics to model workload-related injury risk, and multimodal data to support broader risk modelling approaches (Alzahrani et al., 2026; Kim et al., 2026; Lang et al., 2025; Martins et al., 2025; Ren et al., 2025; González et al., 2024). This body of literature suggests that the integration of wearable sensor data and AI-based modelling is academically and practically significant because it may support more individualized, real-time, and data-informed strategies for athlete monitoring and sports injury prevention.

Despite this promise, the literature presents a complex and methodologically heterogeneous picture. The reviewed studies differ substantially in sensor type, sensor placement, feature extraction, athlete population, sport context, AI or machine learning model, injury-related outcome, and validation approach. Some studies focus on biomechanical risk indicators such as knee abduction moment, landing stability, gait patterns, joint angles, tibial force, or muscle activation, whereas others examine workload-related indicators such as GPS-derived external load, acute-chronic workload ratio, monotony, strain, RPE, cumulative loading, or fatigue-related features (Benjaminse et al., 2024; Kiernan et al., 2018; Tedesco et al., 2020; Carey et al., 2018; Fousekis et al., 2025; de Leeuw et al., 2022). This variation creates an important problem for both research and practice: it is difficult to determine whether reported predictive models are measuring comparable dimensions of injury risk, whether their performance can be generalized across contexts, and whether their outputs can meaningfully inform training decisions. If this problem remains unresolved, AI-driven wearable systems may remain technically promising but insufficiently validated for practical injury prevention. Therefore, a systematic review is needed to synthesize how wearable sensor data are operationalized, how AI/ML models are applied, how outcomes are defined, and how methodological quality is evaluated.

A key gap in the existing literature is that research on AI-driven wearable sensor-based injury prediction remains dispersed across multiple subtopics rather than integrated into a coherent evaluative structure. Some studies emphasize sensor technologies and feature extraction, such as IMU-sEMG integration, insole pressure signals, stretch sensors, or inertial sensor features (Alzahrani et al., 2026; Lang et al., 2025; Ohnishi et al., 2024; Tedesco et al., 2020). Others focus primarily on model comparison, including logistic regression, random forest, support vector machine, XGBoost, Naïve Bayes, LSTM, Transformer, TCN–Transformer, ST-GCN, and ensemble modelling approaches (Carey et al., 2018; Han et al., 2024; Kim et al., 2026; Ren et al., 2025; Ma et al., 2025; Zhao, 2025). A further group of studies focuses on population-specific or sport-specific injury outcomes, such as professional football muscle injury risk, rugby position-specific injury prediction, elite female football non-contact injuries, Taekwondo landing-risk indicators, running-related injury, and overuse injury monitoring (Martins et al., 2025; Ren et al., 2025; González et al., 2024; Kim et al., 2026; Kiernan et al., 2018; de Leeuw et al., 2022). Although these studies contribute important evidence, the literature has not been sufficiently organized around how sensor inputs, AI/ML models, injury outcomes, validation procedures, and implementation barriers should be evaluated together. This fragmentation limits the capacity of the field to move from isolated prediction studies toward a more systematic understanding of AI-driven wearable sensor-based injury risk prediction.

The novelty of this review lies in its integrative and evaluative orientation. Rather than treating wearable sensors, machine learning models, athlete populations, performance metrics, and implementation challenges as separate topics, this review positions them as interrelated components of an emerging injury-risk prediction ecosystem. In this review, five thematic domains are used as an analytical logic to organize and interpret the indicators extracted from the reviewed literature: wearable sensor technologies, sensor placements, and sensor-derived features used for sports injury risk prediction; artificial intelligence and machine learning models applied to wearable sensor-derived data; athlete populations, sport contexts, and injury-related outcomes represented in the literature; model performance, validation procedures, and methodological quality; and methodological challenges, implementation barriers, and integrative framework development. These themes are not presented as an empirical framework directly established in all reviewed studies. Rather, they are used analytically by the authors to synthesize heterogeneous evidence and to develop an integrative framework that connects sensor modality and placement, feature extraction, AI/ML model selection, injury-related outcome definition, model evaluation, and practice-oriented implementation.

Accordingly, this systematic review aims to synthesize the literature on AI-driven wearable sensor data for sports injury risk prediction among athletes and to develop an integrative framework for evaluating this evidence. The review is guided by the following research questions:

1. What types of wearable sensors, sensor placements, and sensor-derived features are used to operationalize sports injury risk prediction among athletes?
2. What artificial intelligence and machine learning models are applied to wearable sensor-derived data for predicting sports injury risk among athletes?
3. Which athlete populations, sport contexts, and injury-related outcomes are represented in AI-driven wearable sensor-based injury risk prediction studies?
4. How are model performance, validation procedures, and methodological quality evaluated in these studies?
5. What methodological limitations, implementation barriers, and practice-oriented considerations should inform the development of an integrative framework for athlete monitoring and sports injury prevention?

By addressing these questions, this review makes three contributions. Theoretically, it advances a multidimensional understanding of sports injury risk as an interaction among biomechanical, physiological, workload-related, athlete-specific, and sport-contextual indicators. Methodologically, it provides a thematic synthesis and integrative evaluation logic for organizing heterogeneous AI-wearable injury prediction studies. Practically, it offers guidance for researchers, sport scientists, coaches, and practitioners in assessing whether AI-driven wearable systems are valid, interpretable, context-sensitive, and suitable for athlete monitoring and injury prevention.

METHOD

Review Design

This study employed a systematic literature review design to identify, select, analyze, and synthesize evidence on artificial intelligence-driven wearable sensor data for sports injury risk prediction among athletes. A systematic review design was appropriate because the topic requires a structured process for collecting and synthesizing evidence across sport science, wearable technology, artificial intelligence, biomechanics, and injury-prevention research.

The review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement to support transparent reporting of record identification, screening, eligibility assessment, and study inclusion (Page et al., 2021). The review scope was structured using the PIOS framework, consisting of Population, Intervention/Index approach, Outcome, and Study design. This framework was adapted from structured question frameworks commonly used to define eligibility criteria and organize systematic review searches (Methley et al., 2014).

The synthesis was conducted using thematic synthesis. This approach was selected because the included studies varied in sport context, athlete population, wearable sensor modality, sensor placement, sensor-derived features, artificial intelligence or machine learning model, injury-related outcome, and validation procedure. Thematic synthesis is suitable for organizing heterogeneous evidence into analytical themes while maintaining a transparent link between extracted data and interpretive synthesis (Thomas & Harden, 2008).

Data Source and Search Strategy

The literature search was conducted using Scopus as the main database. Scopus was selected because it provides broad interdisciplinary coverage across health sciences, sport science, engineering, computer science, and applied technology, making it suitable for reviews involving wearable sensors and artificial intelligence. Previous comparisons of scholarly databases also indicate that Scopus offers broad citation and journal coverage across scientific fields (Falagas et al., 2008). The search strategy was developed based on the review title, research questions, and PIOS framework. Four main concepts guided the construction of the search string: artificial intelligence and machine learning, wearable sensor data, sports injury risk prediction, and athlete populations.

The Boolean search string used in Scopus was as follows: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "predictive model" OR "prediction model" OR classifier) AND ("wearable sensor" OR "wearable device" OR "wearable technology" OR "sensor-derived data" OR "sensor data" OR "inertial measurement unit" OR IMU OR accelerometer OR gyroscope OR GPS OR "heart rate monitor" OR electromyography OR EMG) AND ("injury risk" OR "injury prediction" OR "injury risk prediction" OR "sports injury" OR "athletic injury" OR "musculoskeletal injury" OR "overuse injury") AND (athlete OR athletes OR "student athlete" OR "student-athlete" OR "elite athlete" OR "youth athlete" OR "adolescent athlete" OR "collegiate athlete").

The search string was constructed using Boolean operators and phrase searching compatible with Scopus. The terms were designed to balance sensitivity and specificity by including broad AI-related terms, wearable sensor-related terms, injury-related terms, and athlete-related terms. The initial database search produced 136 records.

Database filters were applied to limit the results to final English-language journal articles. The specific Scopus filter settings included document type, publication stage, source type, and language. All 136 records were subsequently screened based on title, abstract, and metadata. At this stage, 76 records were excluded because they did not sufficiently align with the review focus. The remaining 60 reports were sought for retrieval.

Eligibility Criteria

Eligibility criteria were established based on the research questions, the PIOS framework, the conceptual focus of the review, and the requirements of data extraction and thematic synthesis. Articles were considered eligible for the main extraction and synthesis matrix when they provided sufficient information about athlete populations, wearable sensor-derived data, AI or machine learning models, injury-related prediction outcomes, and methodological or validation characteristics.

Table 1. PIOS Framework for Defining the Review Scope

PIOS Component	Operational Definition in This Review	Application to Article Selection
P – Population	Athletes or athletic populations, including student-athletes, elite athletes, youth athletes, adolescent athletes, collegiate athletes, professional players, or sport-specific athletes	Studies had to involve athletes or sport participants engaged in structured training, competition, sport-specific performance, or athlete monitoring contexts
I – Intervention / Index Approach	Artificial intelligence, machine learning, deep learning, predictive modelling, algorithmic approaches, wearable sensor data, IMU, accelerometer, gyroscope, GPS, EMG/sEMG, heart-rate monitor, pressure sensor, insole sensor, stretch sensor, MEMS sensor, flexible sensor, or other sensor-derived data	Studies had to use AI, machine learning, or related predictive approaches applied to wearable or sensor-derived athlete data
O – Outcome	Sports injury risk prediction, injury risk classification, injury occurrence, injury prevention, musculoskeletal injury risk, ACL risk, overuse injury risk, non-contact injury risk, fatigue-related injury risk, biomechanical injury-risk indicators, or model performance for injury-related prediction	Studies had to report an injury-related predictive outcome or a risk-relevant biomechanical, workload, fatigue, or monitoring indicator
S – Study Design	Empirical studies, predictive modelling studies, validation studies, observational studies, cohort or longitudinal studies, laboratory or field-based modelling studies, AI/ML-based system studies, or applied AI studies	Studies had to provide sufficient methodological and outcome information for structured extraction and thematic synthesis

Articles were included in the main extraction and synthesis matrix if they met the following criteria. First, they had to involve athletes or sport-specific athletic populations. Second, they had to use wearable sensor data or sensor-derived features, including but not limited to IMU, accelerometer, gyroscope, GPS, EMG/sEMG, heart-rate monitoring, insole pressure data, stretch sensors, MEMS sensors, or flexible sensors. Third, they had to apply artificial intelligence, machine learning, deep learning, predictive modelling, classification, regression, or related computational approaches. Fourth, they had to address sports injury risk prediction, injury occurrence, injury-risk classification, injury prevention, or a clearly injury-related predictive indicator. Fifth, they had to provide sufficient extractable information from the title, abstract, metadata, or available study description to support thematic synthesis.

Articles were excluded from the main extraction matrix if they did not focus on athletes or sport-specific populations, did not use wearable or sensor-derived data, did not apply AI or machine learning approaches, or did not address injury risk prediction or an injury-related predictive outcome. Studies focused exclusively on diagnosis, rehabilitation, recovery prediction, return-to-play, movement recognition, general performance optimization, or technology adoption without a clear injury-risk prediction component were not included in the main matrix. However, articles that were conceptually or methodologically relevant but did not fully meet the PIOS criteria were retained as supporting literature when they contributed to the background, discussion, methodological context, or framework development.

Table 2. Inclusion and Exclusion Criteria

Criteria Category	Inclusion Criteria	Exclusion Criteria
Research Focus	Studies examining AI-driven or machine learning-based wearable sensor data for sports injury risk prediction or injury-related risk indicators	Studies unrelated to injury risk prediction or focused only on general athlete monitoring, performance tracking, rehabilitation, or diagnosis
Population Focus	Studies involving athletes, student-athletes, elite athletes, youth/adolescent athletes, collegiate athletes, professional players, or sport-specific athletic populations	Studies involving general populations, clinical patients, rehabilitation patients, or non-athlete users without a clear sport context
Technology Focus	Studies using wearable sensors, wearable devices, wearable technology, IMU, accelerometers, gyroscopes, GPS, heart-rate monitors, EMG/sEMG, pressure sensors, insole sensors, stretch sensors, MEMS sensors, flexible sensors, or other wearable sensor-derived data	Studies using only questionnaires, imaging, non-wearable laboratory instruments, or non-sensor-based data without wearable or sensor-derived input
AI / Model Focus	Studies applying artificial intelligence, machine learning, deep learning, predictive modelling, classification, regression, or algorithmic prediction	Studies using only descriptive statistics, non-predictive monitoring, or non-algorithmic assessment
Outcome Focus	Studies reporting injury risk prediction, injury occurrence, injury risk	Studies focused only on recovery, rehabilitation,

	classification, injury prevention, musculoskeletal injury risk, overuse injury risk, ACL risk, fatigue-related injury risk, biomechanical injury-risk indicators, or prediction performance	diagnosis, return-to-play, activity recognition, or performance optimization without a clear injury-risk component
Publication Type	Final English-language journal articles indexed in Scopus	Non-English publications, non-final records, conference papers, editorials, commentaries, reviews, and non-scholarly documents
Metadata Availability	Articles with sufficient title, abstract, keywords, methodological description, results, or model information for extraction	Articles with insufficient metadata, missing abstracts, or insufficient extractable information
Relevance to Synthesis	Articles contributing evidence to at least one review theme and to the development of the integrative framework	Articles that did not contribute relevant data to the research questions or synthesis framework

Data Synthesis and Framework Development

The 29 articles included in the main extraction matrix were synthesized using thematic synthesis. This method was selected because the included studies varied in terms of sport context, athlete population, wearable sensor technology, sensor placement, sensor-derived feature type, AI/ML model, injury-related outcome, validation procedure, and methodological design. Thematic synthesis enabled the review to organize heterogeneous evidence into coherent analytical themes rather than merely summarizing studies individually.

The synthesis was conducted by mapping the extracted data across the research questions and grouping the evidence into recurring analytical categories. These categories were then organized into five major themes: wearable sensor technologies, sensor placements, and sensor-derived features used for sports injury risk prediction; artificial intelligence and machine learning models applied to wearable sensor-derived data; athlete populations, sport contexts, and injury-related outcomes represented in the literature; model performance, validation procedures, and methodological quality; and methodological challenges, implementation barriers, and integrative framework development.

The final stage of synthesis involved developing an integrative framework for AI-driven wearable sensor-based sports injury risk prediction among athletes. The framework was designed to connect six analytical layers: wearable sensor type and placement, sensor-derived features, AI or machine learning model, injury-related prediction outcome, model evaluation and validation, and practice-oriented implementation. The framework was developed analytically from the synthesis of the included studies. Therefore, it should be understood as a conceptual contribution of this review rather than as an empirical framework directly established in every included article.

RESULTS AND DISCUSSION

Study Selection Results

The study-selection process followed the PRISMA flow structure and narrowed the evidence base from a broad Scopus search into a focused set of studies for extraction and synthesis. The initial Scopus search identified 136 records. No records were removed before screening because no duplicate records were reported, no records were marked as ineligible by automation tools, and no records were removed for other reasons. Therefore, all 136 records were screened based on title, abstract, and metadata. During the screening stage, 76 records were excluded because they did not sufficiently align with the review focus. The remaining 60 reports were sought for retrieval. Of these, 29 reports were not retrieved or were not available for further eligibility assessment, leaving 31 reports to be assessed against the operational PIOS framework. Two reports were excluded because they were not aligned with the operational PIOS framework. Finally, 29 studies met the eligibility criteria and were included in the main review. These 29 studies constituted the evidence base for data extraction, thematic synthesis, and integrative framework development.

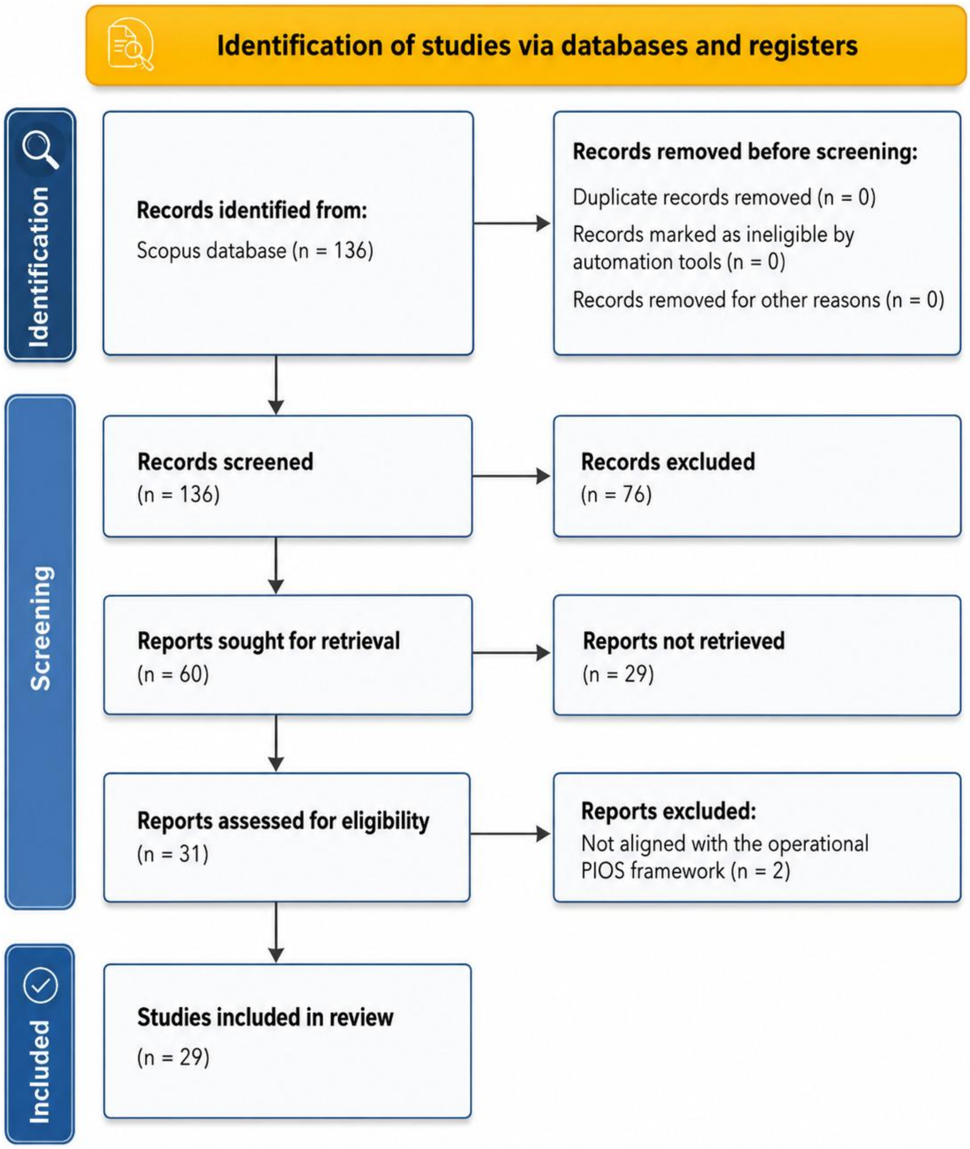

Figure 1. PRISMA flow diagram of record identification, screening, eligibility assessment, and inclusion process.

Characteristics of Included Studies

The 29 included studies covered diverse sport contexts, athlete populations, sensor modalities, AI/ML models, and injury-related outcomes. The studies included team-sport, running, combat-sport, triathlon, volleyball, and general athletic-monitoring contexts. Across these studies, injury risk was operationalized in two main ways. Some studies addressed direct injury prediction, injury-risk classification, injury occurrence, or time-loss injury outcomes. Other studies used proxy injury-risk indicators, such as fatigue state, workload exposure, landing stability, knee abduction moment, knee valgus angle, abnormal movement, post-ACL gait pattern, and biomechanical or neuromuscular risk markers.

Table 3 summarizes the included studies using a condensed extraction matrix. The table preserves the main information needed for synthesis: study design, population and sport context, wearable sensor or data source, sensor-derived features, AI/ML model, and injury-related outcome. Studies with incomplete reporting are marked using cautious wording such as “not specified” or “unclear” to avoid unsupported interpretation.

Table 3. Characteristics of included studies on AI-driven wearable sensor data for sports injury risk prediction

No	Author/Year	Study design	Population and sport context	Wearable sensor/data source	Sensor-derived features	AI/ML model	Injury-related outcome
1	Wang, 2025	Digital twin / predictive modelling	Athletes in competitive sports; Competitive sports	Biomechanical data and real-time monitoring; specific sensor placement not specified	Hamstring force, muscle stiffness, biomechanical simulation data	XGBoost; PCA-based preprocessing; musculoskeletal modelling	Injury risk prediction and management
2	Chen & Wang, 2025	Multisource sensor-based predictive framework	Professional athletes; public datasets also used; Athlete fatigue monitoring	Multi-source sensors: acceleration, heart rate, EMG	Multimodal sequential signals; local muscular fatigue; physiological load	LSTM-GAN; ST-GCN; focal loss	Fatigue state classification as an injury-prevention indicator
3	Benjaminse et al., 2024	Technical note / ML modelling	Talented female football players (n = 32); Football agility task	Xsens wearable sensors; Vicon and force plates also used	Kinematics; knee abduction moment indicators	ML classification/regression models; specific model names not fully specified in abstract	ACL-related knee joint loading / KAM risk indicator

No	Author/Year	Study design	Population and sport context	Wearable sensor/data source	Sensor-derived features	AI/ML model	Injury-related outcome
4	Han et al., 2024	ML predictive modelling	84 active runners; Running	Wearable sensors during laboratory-controlled and outdoor running	Joint angles; GRF; stride length; muscle activation; foot pressure	Ensemble GBDT; LSTM; SVM	Running-related injury prediction
5	Cui et al., 2023	Data analysis / ML-based monitoring	Students/athletes in physical education; Physical education / training	Wearable devices; placement not specified	Exercise volume; heart rate; steps; distance	Time-series analysis; ML algorithms; ANN	Physical recovery and injury-prevention risk
6	Alzahrani et al., 2026	Field experiment / framework validation	50 athletes; Running, jumping, lifting	IMUs on knee, hip, shoulder; sEMG on biceps, triceps, quadriceps	Joint angles; muscle activation; muscle force; asymmetry	Hybrid IMU-sEMG model; adaptive ML optimization	Injury-risk classification, including ACL and muscle-strain risks
7	Gai, 2025	Intelligent system / ML modelling	Athletes; General athletic monitoring	Flexible sensors; placement not specified	Multimodal sport data; improper motion patterns	SVM; LSTM; artificial synapse; feature-level fusion	Improper motion detection and injury risk prediction
8	Li, Hou, Amjad, & Mushtaq, 2025	Multimodal deep learning framework	Athletes; specific population not specified; General sports injury prediction	Wearable IMUs and force-sensitive insoles; placement not specified; CT imaging also included	Joint movement; GRF; loading patterns	Swin-UNet; LSTM; decision-level fusion	Injury-risk score / sports injury prediction
9	Ma, Chen, & Li, 2025	Experimental fatigue-recognition study	15 basketball players; Basketball	Lower-limb sEMG; muscle placement not fully specified	Eight fused sEMG feature types; muscle synergy features	Transformer; compared with LSTM and XGBoost	Lower-limb fatigue as an injury-risk indicator
10	Kim et al., 2026	AI-based EMG analysis	30 elite male Taekwondo athletes; Single-leg landing in Taekwondo	EMG during single-leg landing; muscle placement not specified in abstract	Eight EMG features per muscle per landing phase	Random Forest; XGBoost; Logistic Regression; Voting Classifier; Ridge Regression	Landing stability and injury-risk indicators

No	Author/Year	Study design	Population and sport context	Wearable sensor/data source	Sensor-derived features	AI/ML model	Injury-related outcome
11	Liu & Wang, 2024	Risk assessment and alert-system model	Martial arts athletes; Martial arts	Wearable sensors in 6G network; placement not specified	Temperature; pulse rate; opponent-induced force; ECG	Optimized SVM risk prediction model; VFOA	Athlete risk-level assessment and safety alerts
12	Zhou, 2024	Biomechanical analysis with LSTM	Three groups of athletes; Martial arts whip-leg maneuver	Human motion sensors; EMG-like muscle activation data implied	Action time-series features; muscle activation; leg angles	LSTM optimized using improved particle swarm algorithm	Biomechanical danger of injury from whip-leg maneuver
13	Tedesco et al., 2020	Field-based ML classification	12 male rugby players, healthy and post-ACL; Rugby change-of-direction	Inertial sensors on lower limbs	Time-domain and frequency-domain inertial features	KNN; Naive Bayes; SVM; Gradient Boosting; MLP; stacking	Post-ACL gait-pattern identification
14	Pu & Liu, 2024	Algorithm development / validation	10 healthy subjects for rehabilitation exercises; athletes discussed; Rehabilitation exercises / athlete health management	Wearable devices; placement not specified	Biomechanics data; abnormal joint movement; ICA features	ARNN; RCNN	Injury-risk anomaly detection and rehabilitation monitoring
15	Whelan et al., 2017	Classification methodology comparison	55 healthy volunteers; athlete/patient technique context; Barbell squat / injury-risk screening	IMUs on lumbar spine, both shanks, both thighs	Tri-axial accelerometer, gyroscope, and magnetometer features	Global and personalized Random Forest classifiers	Aberrant squat technique as injury-risk screening indicator
16	Zhu, 2025	System design and experimental evaluation	Athletes; exact sample not specified; General sports management	Wireless sensor networks and wearable devices; placement not specified	Real-time sensor and wearable data	Neural networks / ML analytics layer	Athlete monitoring and injury prediction

No	Author/Year	Study design	Population and sport context	Wearable sensor/data source	Sensor-derived features	AI/ML model	Injury-related outcome
17	Kiernan et al., 2018	Preliminary proof-of-concept / longitudinal monitoring	9 collegiate track athletes; Running	Hip-mounted activity monitor / accelerometer	Estimated peak vGRF; stride number; weighted cumulative loading	Injury-prediction model proposed; specific ML model not applied in abstract	Running-related injury prediction
18	Martinez-Gramage et al., 2020	Intervention plus biomechanical analysis with ML	19 young triathletes; Triathlon running	Surface dynamic EMG and kinematic analysis; placement not specified	Pelvic drop; gluteus medius activation; trunk/knee/ankle variables	Random Forest classification tree	Running injury incidence / prevention
19	Chen & Liu, 2026	IoT and ML system	Athletes; sample not specified; Sports performance tracking	Chest straps; HR monitors; IMUs; accelerometers; GPS trackers	Training load; fatigue; HR/HRV; physiological and biomechanical data	Logistic Regression; Random Forest; XGBoost	Injury prediction and performance monitoring
20	Fousekis et al., 2025	Longitudinal predictive modelling	40 elite soccer players; Professional soccer	GPS	ACWR for distance, speed zones, sprinting, acceleration, deceleration	Binomial logistic regression; ROC analysis	Non-contact injury risk
21	Zhao, 2025	Biomechanical AI modelling	Athletes; sample not specified; General sports biomechanics	Vicon motion capture and Noraxon EMG; wearable status unclear	Joint-angle rate; GRF; EMG activity	SPCA; ST-GCN	Dynamic injury risk prediction
22	de Leeuw et al., 2022	Retrospective personalized ML study	14 elite volleyball players; Professional volleyball	Wearable devices for jump load; manually logged physical load	Jump load; training load; wellness indicators	Subgroup Discovery	Overuse injury emergence/development
23	Lang et al., 2025	Dataset and ML model development	Athletes and patients; exact sport population mixed; In-place running	Wearable insole sensors	Insole pressure signals; vGRF; tibia bone force	TCN-Transformer	Early warnings of fatigue-induced injuries

No	Author/Year	Study design	Population and sport context	Wearable sensor/data source	Sensor-derived features	AI/ML model	Injury-related outcome
24	Ohnishi et al., 2024	Wearable device estimation study	Five healthy male/female participants in twenties; Sports involving jumping and direction changes	Knee supporter with three stretch sensors	Knee flexion and valgus angles	Random Forest Regressor	ACL injury risk estimation / prevention
25	Martins et al., 2025	Four-year longitudinal ML study	96 male professional football players; Professional football	GPS-derived external load; RPE internal load	External and internal workload variables	Kstar classifier and other ML classification methods	Time-loss muscle injury risk
26	Li, Liu, & Yuan, 2021	MEMS sensor and big-data model	Martial arts athletes; Martial arts teaching/training	Multiple MEMS inertial sensors on lower limbs	Acceleration; angular velocity; magnetometer; joint posture angles	Big data analysis; specific model not fully specified	Training performance and injury risk prediction
27	Carey et al., 2018	Predictive modelling over three seasons	Elite Australian football players; Australian football	GPS devices; accelerometers; RPE	Absolute and relative training-load metrics	Regularised logistic regression; GEE; Random Forest; SVM	Non-contact, time-loss, and hamstring injury prediction
28	Ren et al., 2025	ML injury prediction study	63 professional rugby union players; Rugby union	GPS	Total workload; ACWR; monotony; strain	Logistic Regression; Naive Bayes; SVM; Random Forest; XGBoost	Injury prediction by player position
29	Gonzalez et al., 2024	Prospective cohort	24 elite female football players; Football	GPS workload plus clinical and multiomics data	External workload; genetic score; metabolites	Risk model; specific ML algorithm not clearly specified in abstract	Non-contact injury prediction

Wearable Sensor Modalities and Sensor-Derived Features

This theme answers the first research question concerning the types of wearable sensors, sensor placements, and sensor-derived features used to operationalize sports injury risk prediction among athletes. The thematic synthesis showed that the reviewed studies used multiple sensor modalities to capture different dimensions of athlete risk, including workload exposure, biomechanical loading, neuromuscular activation, physiological status, fatigue, and movement quality.

GPS-based systems were mainly used to capture workload-related variables in team-sport contexts. These variables included total workload, acute-chronic workload ratio, distance, speed zones, sprinting, acceleration, deceleration, monotony, strain, external load, and RPE. GPS-derived workload variables were associated with injury prediction, non-contact injury risk, time-loss muscle injury risk, hamstring injury prediction, and position-specific injury prediction in football, soccer, rugby union, and Australian football contexts (Carey et al., 2018; Fousekis et al., 2025; Gonzalez et al., 2024; Martins et al., 2025; Ren et al., 2025).

IMUs, accelerometers, inertial sensors, and MEMS sensors were used to capture movement-related and biomechanical indicators. These sensors were applied in studies on running injury prediction, ACL-related gait-pattern identification, squat technique assessment, martial arts training, and hybrid wearable biomechanics frameworks (Alzahrani et al., 2026; Kiernan et al., 2018; Li, Liu, & Yuan, 2021; Tedesco et al., 2020; Whelan et al., 2017). The extracted features included estimated peak vertical ground reaction force, stride number, weighted cumulative loading, time-domain and frequency-domain inertial features, acceleration, angular velocity, magnetometer-derived data, joint posture angles, and movement-quality indicators.

EMG and sEMG data were used to represent neuromuscular activation, muscle force, muscle synergy, lower-limb fatigue, landing-phase characteristics, and asymmetry. These features appeared in studies involving basketball players, Taekwondo athletes, triathletes, and hybrid IMU-sEMG injury-risk classification systems (Alzahrani et al., 2026; Kim et al., 2026; Ma et al., 2025; Martinez-Gramage et al., 2020). Wearable insole sensors and pressure-related systems were used to estimate lower-limb load, insole pressure signals, vertical ground reaction force, tibia bone force, foot pressure, and loading patterns (Han et al., 2024; Lang et al., 2025). Stretch sensors were used to estimate knee flexion and knee valgus angle in ACL injury-risk estimation or prevention contexts (Ohnishi et al., 2024).

Several studies used multisource or multimodal systems by combining acceleration, heart rate, EMG, IMU, GPS, force-sensitive insoles, chest straps, physiological data, biomechanical data, or medical imaging (Chen & Liu, 2026; Chen & Wang, 2025; Li, Hou, Amjad, & Mushtaq, 2025). Across the evidence base, sensor-derived features were grouped into five recurring categories: workload-related features, biomechanical features, neuromuscular features, physiological features, and movement-quality features. These categories show that sports injury risk was operationalized through multiple measurable indicators rather than through a single uniform variable.

AI/ML Models Used for Injury-Risk Prediction

This theme answers the second research question concerning the artificial intelligence and machine learning models applied to wearable sensor-derived data for predicting sports injury risk among athletes. The included studies applied a broad range of AI and machine learning models, from conventional classifiers and regression models to sequential, graph-based, and multimodal deep-learning architectures.

Conventional machine learning models included logistic regression, regularised logistic regression, binomial logistic regression, random forest, random forest regressor, support vector machine, Naive Bayes, K-nearest neighbor, gradient boosting, XGBoost, ridge regression, Kstar classifier, and ensemble methods. These models were commonly applied when sensor-derived data had been transformed into structured predictors, workload variables, biomechanical indicators, or classification features (Carey et al., 2018; Fousekis et al., 2025; Han et al., 2024; Kim et al., 2026; Ren et al., 2025; Tedesco et al., 2020; Whelan et al., 2017).

More complex architectures were also represented. LSTM models were used in studies involving sequential fatigue, movement, or multimodal sensor data (Chen & Wang, 2025; Gai, 2025; Han et al., 2024; Zhou, 2024). Transformer-based models appeared in lower-limb fatigue recognition and wearable insole-based lower-limb load estimation (Lang et al., 2025; Ma et al., 2025). ST-GCN was used in multisource sensor-based fatigue prediction and biomechanical AI modelling contexts (Chen & Wang, 2025; Zhao, 2025). Other complex modelling approaches included LSTM-GAN, Swin-UNet, ARNN, RCNN, neural network analytics layers, artificial synapse models, PCA-based preprocessing, musculoskeletal modelling, decision-level fusion, and feature-level fusion (Chen & Wang, 2025; Gai, 2025; Li, Hou, Amjad, & Mushtaq, 2025; Pu & Liu, 2024; Wang, 2025; Zhu, 2025).

The results showed no single dominant AI/ML model across the included studies. Instead, model selection varied according to sensor modality, data structure, extracted features, and injury-related target. Conventional models were more commonly associated with structured workload or biomechanical predictors, whereas deep learning, graph-based, sequential, and multimodal fusion models were used for sequential signals, multisource sensor inputs, high-dimensional data, or integrated biomechanical and physiological information.

Athlete Populations, Sport Contexts, and Injury Related Outcomes

This theme answers the third research question concerning athlete populations, sport contexts, and injury-related outcomes represented in AI-driven wearable sensor-based injury risk prediction studies. The included studies represented a range of athlete groups and sport settings rather than a single homogeneous population.

Team-sport contexts included professional football, soccer, rugby union, Australian football, volleyball, and football agility tasks (Benjaminse et al., 2024; Carey et al., 2018; de Leeuw et al., 2022; Fousekis et al., 2025; Gonzalez et al., 2024; Martins et al., 2025; Ren et al., 2025; Tedesco et al., 2020). Running-related contexts included collegiate track athletes, active runners, in-place running, and triathlon running (Han et al., 2024; Kiernan et al., 2018; Lang et al., 2025; Martinez-Gramage et al., 2020). Combat-sport and martial-arts contexts included Taekwondo, martial arts, and whip-leg maneuver analysis (Kim et al., 2026; Li, Liu, & Yuan, 2021; Liu & Wang, 2024; Zhou, 2024). Other contexts included basketball, physical education or training settings, general athletic monitoring, sports management, rehabilitation monitoring, and broad competitive sports settings (Cui et al., 2023; Ma et al., 2025; Pu & Liu, 2024; Wang, 2025; Zhu, 2025).

The injury-related outcomes varied across the included studies. Some studies examined direct injury-related outcomes, including injury prediction, injury-risk classification, non-contact injury risk, time-loss injury, time-loss muscle injury risk, hamstring injury prediction, running-related injury prediction, and injury prediction by player position (Carey et al., 2018; Fousekis et al., 2025; Han et al., 2024; Martins et al., 2025; Ren et al., 2025). Other studies used proxy injury-risk indicators. These included fatigue state classification, lower-limb fatigue, landing stability, ACL-related knee joint loading, knee abduction moment, knee valgus angle, tibial force, abnormal joint movement, improper motion detection, post-ACL gait-pattern identification, aberrant squat technique, workload exposure, muscle activation, and athlete risk-level assessment (Benjaminse et al., 2024; Kim et al., 2026; Lang et al., 2025; Liu & Wang, 2024; Ma et al., 2025; Ohnishi et al., 2024; Tedesco et al., 2020; Whelan et al., 2017).

The thematic synthesis therefore showed that injury risk was not operationalized uniformly across the evidence base. Team-sport workload studies more often focused on injury occurrence, non-contact injury, time-loss injury, or workload-related injury risk. In contrast, studies using EMG/sEMG, IMU, insole sensors, stretch sensors, or movement sensors more frequently measured risk-relevant indicators such as fatigue, knee loading, landing stability, lower-limb load, abnormal movement, or movement-quality features.

Reporting Completeness, Validation, and Methodological Patterns

This theme answers the fourth research question concerning how model performance, validation procedures, and methodological quality were evaluated in the included studies. The extraction matrix showed variation in the completeness of methodological reporting across sample characteristics, sport context, sensor placement, feature extraction, AI/ML model specification, validation procedures, and injury-outcome definitions.

Several studies reported clear information on sample characteristics, sport context, sensor type, and injury-related outcome. These included studies involving collegiate track athletes, active runners, basketball players, elite Taekwondo athletes, elite soccer players, professional football players, professional rugby union players, elite volleyball players, young triathletes, and elite female football players (de Leeuw et al., 2022; Fousekis et al., 2025; Gonzalez et al., 2024; Han et al., 2024; Kiernan et al., 2018; Kim et al., 2026; Ma et al., 2025; Martins et al., 2025; Ren et al., 2025). Other studies provided less complete information in the available study description. Some did not fully specify sample size, athlete subgroup, exact sensor placement, model specification, or validation procedure (Chen & Liu, 2026; Gai, 2025; Wang, 2025; Zhu, 2025).

Sensor placement was reported inconsistently. Some studies specified placement, such as IMUs on the knee, hip, and shoulder; sEMG on selected muscle groups; IMUs on the lumbar spine, shanks, and thighs; lower-limb inertial sensors; hip-mounted activity monitors; and knee-supporter stretch sensors (Alzahrani et al., 2026; Kiernan et al., 2018; Ohnishi et al., 2024; Tedesco et al., 2020; Whelan et al., 2017). In other studies, placement was not specified or was described only generally.

The specification of AI/ML models also varied. Several studies reported clearly defined models, such as logistic regression, random forest, SVM, XGBoost, LSTM, Transformer, TCN-Transformer, ST-GCN, and other named methods. Other studies used broader descriptions, such as neural networks, big data analysis, risk model, or ML algorithms without fully specifying the modelling procedure in the available study description.

Across the included studies, model performance was reported with varying levels of detail. Some studies referred to model comparison, ROC analysis, regression-based prediction, classifier evaluation, or validation-oriented modelling. However, not all studies provided complete information on performance metrics, calibration, external validation, or prospective testing in the available study description. Studies with longitudinal, prospective, or field-based designs tended to provide clearer links between sensor-derived predictors and injury-related outcomes. In contrast, system-design, algorithm-development, and framework-oriented studies more often emphasized model architecture or monitoring function without equally detailed validation information. This variation was treated as part of the methodological pattern identified through the thematic synthesis.

Framework Related Synthesis of Results

This theme answers the fifth research question concerning methodological limitations, implementation barriers, and practice-oriented considerations that should inform the development of an integrative framework for athlete monitoring and sports injury prevention. In the Results section, these elements are reported as descriptive findings from the thematic synthesis rather than as recommendations.

The framework-related synthesis identified six recurring components across the included studies: sensor modality and placement, sensor-derived features, AI/ML model type, injury-related outcome, validation and reporting completeness, and athlete-monitoring context. These components appeared repeatedly across the extraction matrix, although they were not reported with equal completeness in all studies.

The first component was sensor modality and placement. The included studies used GPS, IMU, accelerometers, inertial sensors, EMG/sEMG, wearable insoles, stretch sensors, MEMS sensors, heart-rate-related devices, and multimodal sensor systems. However, sensor placement was not consistently reported across all studies. The second component was sensor-derived features, including workload exposure, ACWR, RPE, joint angles, ground reaction force, muscle activation, fatigue indicators, landing stability, knee valgus angle, knee abduction moment, tibial force, abnormal movement, and movement-quality indicators.

The third component was AI/ML model type. The evidence base included both conventional models and more complex deep learning or multimodal architectures. The fourth component was injury-related outcome. The included studies used both direct injury outcomes and proxy injury-risk indicators. The fifth component was validation and reporting completeness, which varied across studies in relation to sample description, feature extraction, model specification, validation procedure, and outcome definition. The sixth component was athlete-monitoring context, which differed across sport type, athlete population, competitive level, and movement task.

The thematic synthesis also identified several framework-related constraints. These included incomplete reporting of sensor placement, inconsistent specification of sensor-derived features, variation in AI/ML model reporting, heterogeneous injury-outcome definitions, uneven validation detail, and differences in athlete populations and sport contexts. From a practice-oriented perspective, the included studies varied in the extent to which they reported information needed for athlete-monitoring application, such as real-time data capture, interpretability of model outputs, sensor usability, sport-specific applicability, and clarity of decision-relevant injury-risk indicators. These findings formed the descriptive basis for the integrative framework.

DISCUSSION

The first major finding of this review is that sports injury risk was not operationalized as a single directly observable construct, but as a multidimensional pattern derived from workload exposure, biomechanical loading, neuromuscular activation, physiological fatigue, and movement quality. This is theoretically important because it supports a systems-based interpretation of injury risk, in which injury emerges from the interaction between external load, internal response, movement mechanics, tissue tolerance, and sport-specific exposure. Studies using GPS and workload-related indicators, such as external load, ACWR, monotony, strain, RPE, and cumulative loading, conceptualized injury risk mainly as an exposure-management problem in football, rugby, Australian football, and volleyball contexts (Carey et al., 2018; de Leeuw et al., 2022; Fousekis et al., 2025; González et al., 2024; Martins et al., 2025; Ren et al., 2025). In contrast, studies using IMU, EMG/sEMG, wearable insoles, and stretch sensors conceptualized risk through biomechanical and neuromuscular markers, including knee abduction moment, knee valgus angle, tibial force, landing stability, fatigue, and movement abnormality (Alzahrani et al., 2026; Benjaminse et al., 2024; Kim et al., 2026; Lang et al., 2025; Ma et al., 2025; Ohnishi et al., 2024; Tedesco et al., 2020). The similarity across these studies lies in their shared effort to transform sensor data into injury-relevant indicators; the difference lies in the level of proximity to actual injury occurrence. Workload-based studies more frequently linked predictors to direct injury outcomes, whereas biomechanical and neuromuscular studies more often relied on proxy indicators. This difference is scientifically plausible because injury incidence requires longitudinal surveillance, while biomechanical or fatigue indicators can be captured in shorter laboratory or field tasks. A limitation of the present review is that some included studies did not fully report sensor placement or feature-engineering procedures, making it difficult to evaluate the exact measurement validity of the risk indicators. Theoretically, this finding supports an integrated model of injury risk; practically, it suggests that wearable sensor outputs should be interpreted according to the specific mechanism they represent rather than treated as interchangeable injury predictors.

The second finding concerns the diversity of AI and machine learning models applied to wearable sensor-derived data. The significance of this finding is that model choice in AI-driven injury prediction appears to be shaped by data structure and prediction target, not by a single universally superior algorithm. Conventional models such as logistic regression, random forest, support vector machine, Naive Bayes, KNN, XGBoost, gradient boosting, ridge regression, and ensemble methods were generally applied when sensor-derived signals had been transformed into structured predictors, such as workload ratios, biomechanical variables, or classification features (Carey et al., 2018; Fousekis et al., 2025; Han et al., 2024; Kim et al., 2026; Ren et al., 2025; Tedesco et al., 2020; Whelan et al., 2017). By contrast, LSTM, Transformer, TCN-Transformer, ST-GCN, LSTM-GAN, Swin-UNet, ARNN, RCNN, and multimodal fusion models were more commonly used when the data were sequential, high-dimensional, multimodal, or spatial-temporal (Chen & Wang, 2025; Gai, 2025; Lang et al., 2025; Li, Hou, Amjad, & Mushtaq, 2025; Ma et al., 2025; Pu & Liu, 2024; Wang, 2025; Zhao, 2025; Zhou, 2024). This pattern is consistent with the logic of machine learning theory: simpler models can be appropriate for structured tabular features, while temporal and graph-based architectures are more suitable for complex movement sequences or multisource signals. Worsey et al. (2021) similarly emphasized that athlete-monitoring models are sensitive to individual variability, while Johnson et al. (2019) showed that deep learning can support field-based workload and knee-injury risk monitoring when exposure data are temporally structured. The difference among studies may be explained by sample size, dimensionality of input signals, sensor modality, and whether the target outcome was injury occurrence or a proxy risk indicator. The weakness of the present synthesis is that several studies did not provide complete information on model tuning, calibration, imbalance handling, or external testing. Methodologically, the implication is that AI-wearable injury prediction should not be evaluated only by model type or reported accuracy, but by alignment among sensor data structure, model architecture, validation design, and intended injury-related outcome.

The third finding shows that athlete population, sport context, and injury-related outcome strongly determine how wearable AI-based injury prediction should be interpreted. The theoretical meaning of this finding is that injury risk is context-sensitive rather than universal. In ecological and sport-specific models of athlete monitoring, the same sensor variable may carry different meanings depending on sport task, athlete level, sex, exposure pattern, and injury mechanism. Team-sport studies tended to focus on workload-related outcomes such as non-contact injury risk, time-loss injury, muscle injury, hamstring injury, or player-position-specific risk in football, soccer, rugby union, Australian football, and volleyball (Carey et al., 2018; de Leeuw et al., 2022; Fousekis et al., 2025; González et al., 2024; Martins et al., 2025; Ren et al., 2025). Running-related studies emphasized cumulative loading, estimated vertical ground reaction force, tibial force, insole pressure, and lower-limb load (Han et al., 2024; Kiernan et al., 2018; Lang et al., 2025; Martínez-Gramage et al., 2020). Combat-sport and martial-arts studies focused on landing stability, fatigue, whip-leg biomechanics, movement danger, and safety alerts (Kim et al., 2026; Li, Liu, & Yuan, 2021; Liu & Wang, 2024; Ma et al., 2025; Zhou, 2024). These studies are similar in treating injury risk as measurable through athlete-monitoring data, but they differ in how close the outcome is to actual injury. Direct injury prediction was more visible in longitudinal workload studies, whereas proxy outcomes were more common in biomechanical or neuromuscular studies. This difference may be caused by differences in follow-up duration, injury incidence, study setting, and feasibility of collecting verified injury outcomes. Adjacent sport-injury literature also indicates that injury mechanisms vary across age, sex, sport, and exposure type, especially in handball injury, shoulder injury, and knee-injury prevention studies (Aasheim et al., 2018; Achenbach et al., 2018; Andersson et al., 2017; Andersson et al., 2018; Asker et al., 2017). A limitation of the present review is the uneven representation of athlete groups, with some studies involving elite or professional athletes and others using general athletes, healthy participants, or mixed populations. The implication is that theoretical models and practical monitoring systems should not generalize AI-wearable outputs across sports without considering population and task specificity.

The fourth finding concerns the uneven reporting of model performance, validation procedures, and methodological quality. Its significance is that technical sophistication in AI-wearable injury prediction has developed faster than standardized reporting and validation practice. Some studies provided clearer links between sensor-derived predictors and injury-related outcomes through longitudinal, prospective, field-based, or validation-oriented designs, such as Australian football training-load injury modelling, running injury prediction, professional soccer external-load ratios, professional football muscle injury prediction, rugby GPS-derived injury modelling, and elite female football non-contact injury prediction (Carey et al., 2018; Fousekis et al., 2025; González et al., 2024; Kiernan et al., 2018; Martins et al., 2025; Ren et al., 2025). Other studies were more system-oriented or algorithm-development oriented, emphasizing digital twin modelling, intelligent monitoring systems, wearable device algorithms, flexible sensor systems, or IoT-based frameworks without equally detailed evidence of external validation or prospective injury follow-up (Chen & Liu, 2026; Gai, 2025; Pu & Liu, 2024; Wang, 2025; Zhu, 2025). The similarity across these studies is their use of AI/ML to transform sensor data into injury-relevant outputs; the difference is the strength of validation evidence. Studies such as Tedesco et al. (2020) and Whelan et al. (2017) demonstrated classification of movement or technique-related patterns, but these outputs are not identical to prospective injury prediction. Similarly, Benjaminse et al. (2024), Kim et al. (2026), and Ohnishi et al. (2024) identified biomechanical or neuromuscular risk indicators, but the connection between these indicators and actual injury depends on the validity of the assumed risk pathway. The scientific reasons for these differences may include sample size, class imbalance, rare injury events, limited follow-up periods, heterogeneous outcome definitions, and variation in sensor configuration. A weakness of this review is that it relied on available reporting, and some abstracts or metadata did not fully describe performance metrics, calibration, external testing, or feature extraction. Methodologically, the implication is that future evaluation of AI-wearable injury prediction must treat validation quality, calibration, and reporting completeness as central components of evidence quality, not as secondary technical details.

The fifth finding relates to the framework-oriented synthesis, which identified six recurring layers: sensor modality and placement, sensor-derived features, AI/ML model type, injury-related outcome, validation and reporting completeness, and athlete-monitoring context. The meaning of this finding is that AI-driven wearable injury prediction cannot be evaluated adequately by examining sensors, features, models, or outcomes in isolation. Theoretically, this supports an integrative systems perspective in which injury prediction is produced through the interaction between measurement technology, biological meaning, computational modelling, and contextual interpretation. Multimodal studies support this perspective because they combined physiological, biomechanical, imaging, inertial, and neuromuscular data to represent a broader risk profile (Alzahrani et al., 2026; Chen & Liu, 2026; Chen & Wang, 2025; Gai, 2025; Li, Hou, Amjad, & Mushtaq, 2025). However, single-modality or narrower data-stream studies, such as GPS workload modelling or wearable insole estimation, offered a more focused and interpretable pathway from sensor input to risk-related output (Carey et al., 2018; Fousekis et al., 2025; Lang et al., 2025; Martins et al., 2025; Ren et al., 2025). The similarity lies in their aim to generate injury-relevant monitoring information; the difference lies in the trade-off between breadth of measurement and interpretability. Multimodal systems may capture more dimensions of risk, but they also increase data complexity, sensor burden, and modelling opacity. Single-modality systems may be easier to interpret but may miss important physiological or biomechanical mechanisms. These differences are likely shaped by device availability, sport setting, technical infrastructure, and analytical objective. Implementation-oriented injury-prevention literature similarly shows that practical uptake depends on contextual fit, user acceptance, and integration into training routines (Ageberg et al., 2022; Moesch et al., 2022). Digital health and biomarker studies also suggest that data systems become meaningful only when outputs are interpretable and shareable (Domel et al., 2021; Jacob et al., 2022). A limitation is that implementation barriers were often inferred from reporting patterns rather than directly assessed in all included studies. The implication is that the integrative framework should evaluate not only predictive performance, but also sensor usability, interpretability, sport specificity, and decision relevance.

Overall, the findings support the argument that AI-driven wearable sensor data provide a promising but methodologically heterogeneous basis for sports injury risk prediction among athletes. The field is moving from descriptive athlete monitoring toward predictive and risk-oriented modelling, but its scientific value depends on the coherence among sensor selection, feature extraction, model architecture, outcome definition, and validation strategy. This conclusion is consistent with studies showing that wearable technologies can capture sport-specific movement, workload, and physiological information (Liu et al., 2021; Sheridan et al., 2025; Tang, 2024), and with machine-learning studies demonstrating the potential of computational models in injury prediction, athlete monitoring, and performance-related risk assessment (Choi et al., 2025; Johnson et al., 2019; Raju et al., 2026). However, the present synthesis differs from broader digital sport technology reviews because it focuses specifically on how AI-wearable evidence can be evaluated as an integrated injury-risk prediction system rather than as a collection of separate technologies (Mechita et al., 2025). The difference arises from the thematic synthesis approach, which organized evidence according to sensors, features, AI/ML models, injury-related outcomes, validation, and implementation readiness. The major weaknesses of this review include reliance on Scopus-indexed literature, incomplete reporting in some included studies, variation in outcome definitions, uneven population representation, and variable validation depth. These limitations do not invalidate the synthesis, but they constrain the strength of generalization across sports and athlete groups. Theoretically, the review contributes to a multidimensional understanding of injury risk as a sensor-model-outcome system. Practically, it suggests that AI-wearable systems should be interpreted as decision-support tools that require biomechanical plausibility, methodological transparency, validation evidence, and sport-specific contextual judgment before being used in athlete monitoring and injury prevention.

CONCLUSION

This systematic literature review concludes that artificial intelligence-driven wearable sensor data provide a promising but methodologically heterogeneous foundation for sports injury risk prediction among athletes. The review addressed its main objective by showing that injury risk is not captured through a single sensor, model, or outcome, but through an integrated relationship among wearable sensor modalities, sensor-derived features, AI/ML modelling approaches, injury-related outcomes, validation procedures, and athlete-monitoring contexts. Across the reviewed evidence, sports injury risk was commonly operationalized through biomechanical loading, neuromuscular activation, physiological fatigue, movement quality, and workload exposure.

The main scientific contribution of this review is the development of an integrative evaluation perspective for AI-wearable-based injury prediction. The findings suggest that predictive value should not be assessed solely through algorithmic performance, but also through the relevance of sensor placement, the validity of extracted features, the clarity of injury-outcome definitions, the quality of validation procedures, and the practical interpretability of model outputs. Theoretically, this review supports a multidimensional understanding of injury risk as a sensor-model-outcome system. Methodologically, it emphasizes the need for more transparent reporting of sensor configuration, feature engineering, model specification, validation design, and performance metrics.

This review is limited by its reliance on Scopus-indexed literature and by incomplete reporting in several included studies, particularly regarding sensor placement, external validation, and prospective injury follow-up. Future research should prioritize multi-site prospective studies, standardized injury definitions, clearer reporting of wearable sensor protocols, explainable AI approaches, and sport-specific validation frameworks. Such efforts are needed to strengthen the credibility, comparability, and practical usefulness of AI-driven wearable sensor systems for athlete monitoring and injury prevention.

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