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From Monitoring to Prevention: Wearable Technology for Injury Prevention in Sport: A Narrative Review

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Abstract
Background
Wearable technologies are used in sport to monitor training load, biomechanics, physiology, and recovery, but their effectiveness in injury prevention remains uncertain.
Aim
To evaluate evidence on wearables for sports injury prevention using a framework covering measurement validity, injury association, prognostic modelling, implementation, and intervention effectiveness.
Material and methods
A narrative review of wearables monitoring modifiable injury-related factors was conducted. Findings were organized across five translational levels, from measurement validity to injury reduction, following SANRA recommendations [20].
Results
Validity and reliability depend on the device, algorithm, sensor placement, and sporting task. Associations between wearable-derived metrics and injuries are inconsistent and do not support universal risk thresholds. Machine-learning models show promise, but their use is limited by poor external validation, calibration, and methods. Implementation, organizational context, and human decision-making affect practical value. Direct evidence that wearable-guided interventions reduce injuries remains scarce.
Conclusions
Wearables should be viewed as monitoring and decision-support tools rather than autonomous injury-prevention systems. Evidence is strongest for measurement and weakens toward injury reduction. Future research should prioritize multicentre validation, causal modelling, standardized reporting, and pragmatic trials.

Key words: wearable sensors, sports injury prevention, athlete monitoring, training load, biomechanics, machine learning, decision support, implementation science.

1. Introduction

The widespread availability of wearable devices has fundamentally changed the way athletes are monitored during training and competition. What was once reserved for elite sport is now routinely used by recreational athletes and coaches at all performance levels. Their popularity results primarily from their ability to monitor training continuously, evaluate performance, and provide information about fatigue, workload and recovery [1-3].

At the same time, sports injuries remain one of the greatest challenges in both professional and recreational sport. They interrupt training, reduce athletic performance and often require long periods of rehabilitation. Current evidence shows that injuries rarely result from a single cause. Instead, they develop through the interaction of multiple factors, including training load, individual athlete characteristics, previous injuries, recovery status and the specific demands of a given sport [4-6]. Therefore, identifying potential risk factors alone is insufficient. Effective injury prevention requires interventions that have been shown to reduce injury incidence or severity.

The rapid development of wearable technologies has led to growing interest in their potential role in injury prevention. Modern devices enable continuous monitoring of external workload, movement characteristics, physiological responses and selected indicators of recovery and readiness to train [1,7,8]. These data may support individualized training programmes and facilitate the early detection of unfavorable changes in an athlete's condition. However, collecting data should not be confused with preventing injuries. The clinical value of wearable technologies depends not only on measurement accuracy but also on the appropriate interpretation of the collected information and its integration into everyday coaching and medical practice [2,7].

Systematic reviews demonstrate substantial heterogeneity in wearable devices, monitored variables, data-processing methods and injury definitions, making comparisons across studies challenging [2,3,9]. Moreover, the relationship between training load and injury risk is inconsistent and influenced by multiple factors, including fitness level, previous workload, recovery status, injury history and sport-specific demands [10,11].

Artificial intelligence and machine-learning techniques have further expanded the possibilities of integrating wearable-derived data with physiological and clinical information. Nevertheless, good predictive performance does not necessarily translate into clinical usefulness. Many prediction models are based on relatively small cohorts, lack external validation and have not demonstrated that their implementation improves clinical decision-making or reduces injury burden [12,13]. Consequently, the greatest challenge is no longer collecting large amounts of data, but transforming these data into meaningful decisions that improve athlete health and performance.

Wearable technologies should therefore be considered as decision-support tools rather than autonomous injury-prediction systems. Their greatest value lies in providing objective information that, when interpreted together with clinical expertise and coaching experience, may improve training management and contribute to reducing injury risk.

The aim of this narrative review is to critically evaluate the current evidence regarding wearable technology in sports injury prevention. Specifically, the review examines evidence across five translational levels: measurement validity, association with injury, prognostic performance, decision impact, and demonstrable reduction in injury incidence, severity and burden.

2. Material and methods

2.1. Review design and reporting approach

The present review adapts established prevention and implementation frameworks to organize evidence from measurement validity (Level 1) through causal, prognostic, and implementation questions (Levels 2–4) to demonstrable injury reduction (Level 5) [4, 6]. The review was planned and reported with attention to the SANRA domains for transparent and scientifically useful narrative reviews. [20]

2.2. Information sources and search strategy

A comprehensive literature search was conducted across major electronic databases, including PubMed/MEDLINE, Web of Science, and Scopus, to identify relevant peer-reviewed publications. The search strategy employed combinations of medical subject headings (MeSH) and free-text keywords, including: *wearable sensors*, *inertial measurement units*, *GPS*, *sports injury prevention*, *training load*, *biomechanics*, *machine learning*, and *athlete monitoring*. The literature search was structured around a core bibliography of 35 primary sources, supported by 2 methodological and contextual sources. Comprehensive bibliographic verification and active DOI tracking were conducted up to July 12, 2026.

2.3. Eligibility criteria and study selection

Studies were eligible for inclusion if they investigated wearable technologies utilized to measure modifiable factors directly related to musculoskeletal injuries during training and competition.

Studies were excluded if they focused exclusively on post-injury rehabilitation, general disease diagnostics, smartphone applications lacking a body-worn sensor, or wearable devices evaluated solely for performance metrics without an explicit link to workload, biomechanics, injury risk, or preventive action.

2.4. Critical appraisal and narrative synthesis

The narrative synthesis was designed to consistently and rigorously differentiate between monitoring, prediction, decision impact, and actual injury prevention. To guide the argumentation without conducting formal GRADE or risk-of-bias assessments, sources were categorized by priority (Priority A: key to the core argument; Priority B: strong supportive evidence). Special emphasis was placed on the critical appraisal of machine learning models, specifically evaluating sample sizes, class imbalances, calibration reporting, and the presence of independent external validation.

2.5. Data extraction and evidence mapping

Data extraction was systematically organized to follow the translational pathway from conceptual/etiological frameworks to empirical injury outcomes. For each included source, data were extracted regarding:

- Source identity and study design.
- Target population and data characteristics.
- Technology type and underlying construct (e.g., distinguishing external work performed from internal physiological responses).
- Key findings and their specific relevance to the review.
- Assigned evidence level/priority and primary methodological limitations.

3. Wearable-derived measures relevant to injury prevention

3.1. External load and sport exposure

External load represents the physical work performed by an athlete during training or competition and constitutes one of the most frequently monitored constructs using wearable technologies. Modern wearable systems equipped with global positioning systems (GPS), global navigation satellite systems (GNSS), inertial measurement units (IMUs), accelerometers, and local positioning systems enable continuous quantification of variables such as total distance, high-speed running distance, sprint frequency, acceleration and deceleration counts, changes of direction, player load, and mechanical workload [1,7,8,11,21,22].

External load represents the work performed, whereas internal load reflects the athlete-specific response; neither construct should be treated as a direct measure of tissue damage or injury risk. Rather, the biological consequences of a given workload depend on individual tissue capacity, physiological adaptation, recovery status, previous injury, and numerous contextual factors [1,7,8,11,21]. Vanrenterghem et al. proposed a conceptual distinction between biomechanical and physiological load, demonstrating that identical external workloads may produce substantially different mechanical stresses on specific tissues depending on movement strategy and individual characteristics [8]. Likewise, Impellizzeri et al. emphasized that external load represents the training stimulus, whereas internal load reflects the athlete's individual response to that stimulus [7].

Although wearable-derived external-load metrics have repeatedly been associated with injury occurrence, the available evidence remains heterogeneous. Systematic reviews indicate that relationships between workload and injury vary according to sport, injury definition, monitoring window, analytical methods, and athlete characteristics, precluding the establishment of universal workload thresholds applicable across populations [10,23-28]. Consequently, wearable-derived workload measures should be regarded as valuable monitoring tools that contribute to injury risk assessment rather than as direct predictors of injury.

3.2. Movement, biomechanics, gait and technique

Wearable technologies have substantially expanded field-based biomechanical assessment through inertial and related sensors, although measurement accuracy depends on sensor placement, sampling, signal processing, and task-specific validation. These technologies, including IMUs, pressure insoles, foot-mounted sensors, wearable electromyography systems, and advanced GPS devices, allow continuous measurement of spatiotemporal gait parameters, joint kinematics, movement symmetry, impact loading, cadence, ground contact time, and sport-specific movement patterns outside laboratory environments [3,9,29].

Systematic reviews consistently demonstrate that wearable sensors can provide valid and reliable biomechanical information when appropriately validated for a specific device, movement task, and sporting context [3,9,22,29,30]. Nevertheless, substantial methodological heterogeneity persists regarding hardware specifications, sensor placement, signal-processing algorithms, feature extraction methods, and outcome definitions, limiting direct comparisons between studies and reducing the generalizability of findings [3,9,29].

Importantly, accurate biomechanical measurement does not automatically translate into injury prevention. Wearable systems can identify potentially unfavorable movement characteristics, monitor technique changes associated with fatigue, and quantify exposure to repetitive mechanical loading, but evidence directly linking wearable-derived biomechanical variables to future injury remains limited and inconsistent [3,9]. Therefore, biomechanical metrics should primarily be interpreted as proxies for movement quality that require integration with physiological, clinical, and contextual information before informing preventive interventions.

3.3. Physiological response, recovery proxies and readiness indicators

While external load quantifies the work performed, internal load reflects the athlete's physiological and psychological response to that workload. Contemporary wearable devices estimate numerous indicators related to cardiovascular function, autonomic nervous system activity, sleep characteristics, heart rate variability (HRV), energy expenditure, skin temperature, and recovery status, often integrating these variables into proprietary readiness or recovery scores [1,7,8,11,21].

Despite their widespread adoption in elite sport, current evidence advises caution when interpreting these composite indicators. Consensus statements emphasize that internal load, recovery status, and readiness represent multidimensional constructs that cannot be adequately captured by any single physiological variable [1,11]. Furthermore, Passfield et al. questioned the assumption that training load itself constitutes a single universal construct, arguing that physiological adaptation depends on multiple interacting biological mechanisms rather than a single measurable parameter [21].

The complex systems perspective further suggests that injury emerges from dynamic interactions among workload, recovery, adaptation, previous injury, tissue capacity, environmental influences, and individual susceptibility rather than from isolated physiological markers [31,32]. Consequently, commercially available readiness scores should not be interpreted as direct estimates of injury risk. Instead, physiological monitoring should be incorporated into a broader decision-support framework combining external load, biomechanical assessment, medical evaluation, and athlete-reported outcomes [1,6-8,11,21,32].

3.4. Multimodal data integration and contextual variables

One of the major advantages of wearable technology lies in its ability to integrate multiple streams of information collected continuously under real-world sporting conditions. Contemporary athlete monitoring systems combine external-load metrics, biomechanical variables, physiological responses, subjective wellness measures, previous injury history, competition schedules, environmental conditions, and contextual characteristics into comprehensive decision-support platforms [1,3,7,8,11,21].

Within this framework, rather than viewing external and internal load as independent constructs, their integration is essential to capture how physical exposure translates into systemic and localized fatigue [7,21]. Because external load does not reflect the actual mechanical stress experienced by specific musculoskeletal tissues, combining these metrics with biomechanical parameters and physiological indicators allows for a more comprehensive profiling of cumulative tissue-specific load [3,8].

This multimodal approach aligns with contemporary conceptual models of sports injury, which emphasize that injury risk is dynamic and depends heavily on individual modifiers such as physical fitness, historical exposure, and transient fatigue. Rather than relying on rigid, single-metric thresholds, the integration of diverse data sources from wearable sensors enables a more granular and continuous assessment of how an athlete adapts to training demands over time [5,24,31,32].

4. Evidence across the translational pathway from monitoring to prevention

4.1. Level 1: Measurement validity, reliability and agreement

The first stage of the translational pathway concerns the ability of wearable technologies to generate accurate, reliable, and reproducible measurements under sport-specific conditions. Advances in GPS/GNSS systems, inertial measurement units (IMUs), pressure insoles, and wearable biomechanical sensors have substantially improved the capacity to quantify external load, movement characteristics, and physiological responses during training and competition [2,3,9,22,29,30]. However, the quality of subsequent analyses depends fundamentally on the validity and reliability of these primary measurements.

Measurement error is device-, task-, and velocity-dependent; therefore, validity evidence should be specific to the hardware, algorithm, placement, and sporting movement under study [3,9,22,29,30]. Validation studies have demonstrated that measurement accuracy differs across sensor generations, movement types, sampling frequencies, and processing algorithms, making direct comparisons between devices inappropriate without prior verification [9,22,29,30]. Likewise, systematic reviews emphasize considerable methodological heterogeneity in wearable applications, highlighting the importance of transparent reporting of sensor placement, calibration procedures, signal-processing methods, and outcome definitions [3,9,29].

Although many wearable technologies now demonstrate acceptable analytical performance, accurate measurement alone does not establish clinical usefulness or injury-prevention effectiveness. Rather, measurement validity represents the essential first step upon which all subsequent stages of injury-risk assessment and preventive decision-making depend [3].

4.2. Level 2: Associations with injury outcomes and putative risk markers

Once measurement validity has been established, wearable-derived variables can be examined for their association with subsequent injury outcomes. Numerous observational studies have investigated relationships between workload, biomechanical parameters, physiological responses, and musculoskeletal injuries across a variety of sporting populations [10,23-28]. These investigations collectively suggest that injury risk is multifactorial and influenced by interactions among training exposure, recovery, tissue capacity, previous injury, and individual susceptibility [10,23,24].

Associations between workload metrics and injury vary across populations, outcomes, aggregation windows, and analytical choices, precluding universal thresholds for safe or unsafe exposure [10,23-28]. For example, while several cohort studies reported positive associations between cumulative workload or player-load metrics and injury occurrence, the magnitude and direction of these relationships differed according to sport, sex, competitive level, injury definition, and statistical modelling strategy [25-28]. Evidence from female collegiate soccer players further demonstrated that cumulative player load and total distance were associated with lower-extremity injuries, whereas the acute-to-chronic workload ratio was not, illustrating the inconsistency of proposed workload indicators across populations [27].

Overall, current evidence supports the use of wearable-derived metrics as indicators that may contribute to injury-risk estimation rather than as independent causal determinants of injury.

4.3. Level 3: Prognostic modelling, calibration and external validation

The increasing availability of longitudinal wearable datasets has facilitated the development of prognostic models based on conventional statistical approaches and machine-learning algorithms. These models aim to combine multiple workload, biomechanical, and physiological variables to estimate an athlete's future injury probability and thereby support individualized decision-making [12,13,33-35].

Although machine-learning models can identify predictive patterns, the literature is limited by small samples, class imbalance, incomplete calibration assessment, and scarce independent external validation [12,13,33-35]. Existing studies demonstrate that injury prediction from wearable-derived data is technically feasible, yet systematic reviews consistently identify substantial methodological limitations, including high risk of bias, overfitting, inadequate reporting, and poor generalizability across different sporting populations [12,13,35]. Furthermore, most published models have been developed using single-club or single-season datasets, limiting their transportability to broader athletic settings [33,34].

Importantly, discrimination alone does not establish clinical or operational utility; calibrated risk estimates, external validation, and decision-curve or impact analyses are required before deployment [13,32,35]. High values of discrimination metrics, such as the area under the receiver operating characteristic curve, do not guarantee that model-guided interventions improve athlete outcomes or reduce injury burden. Contemporary methodological frameworks therefore emphasize that prognostic performance should be evaluated alongside calibration, clinical usefulness, and implementation feasibility before predictive models are incorporated into routine sports medicine practice [13,32,35].

4.4. Level 4: Decision impact, behaviour change and implementation

The successful translation of wearable-derived information into injury prevention depends not only on predictive performance but also on how monitoring results influence clinical and coaching decisions. Even highly accurate measurements or prognostic models cannot improve athlete outcomes unless they trigger timely, appropriate, and feasible interventions within the sporting environment [6,16,36].

The impact of monitoring depends on who receives the information, how it is interpreted, which action is triggered, and whether the intervention fits the culture and resources of the sporting organization [6,36]. The Translating Research into Injury Prevention Practice (TRIPP) framework highlights implementation as a critical stage connecting scientific evidence with practical injury prevention [6]. Survey data from elite European football clubs similarly demonstrate that although external-load monitoring is widely adopted, the interpretation of wearable-derived information and subsequent decision-making vary considerably according to organizational culture, available expertise, financial resources, and multidisciplinary collaboration [36].

Consequently, wearable technologies should be regarded as decision-support systems that complement rather than replace the expertise of coaches, sports scientists, and medical professionals.

4.5. Level 5: Intervention effectiveness—injury incidence, severity and burden

The highest level of translational evidence requires demonstration that wearable-guided interventions directly reduce injury incidence, severity, or overall burden. Despite the rapid expansion of wearable monitoring technologies, relatively few randomized or pragmatic intervention studies have evaluated this final step of the evidence pathway [3,16].

Direct intervention evidence remains sparse: in a randomized trial of wearable-based feedback, the intention-to-treat analysis did not show a significant reduction in running injuries, while implementation fidelity, including correct device configuration and participant adherence, materially influenced secondary analyses [16]. These findings highlight the distinction between successful monitoring and effective prevention, indicating that wearable technologies currently provide stronger evidence for supporting monitoring and decision-making than for directly reducing sports injuries. Future research should therefore prioritize well-designed multicentre implementation studies and pragmatic randomized trials capable of evaluating both clinical effectiveness and real-world applicability [3,6,13,16,35,36].

5. Barriers to translating monitoring into prevention

5.1. Construct validity and tissue-specific relevance

A major limitation of wearable monitoring is that measured variables are often indirect indicators rather than direct measures of tissue loading or injury mechanisms. Wearable-derived external-load metrics are proxies whose tissue-specific meaning depends on biomechanics, anatomy, adaptation, and the validity of the underlying construct [3,7,8,21]. Therefore, workload metrics should be interpreted together with biomechanical and physiological information rather than as standalone indicators of injury risk.

5.2. Causal inference in adaptive training environments

Most evidence linking wearable-derived metrics with injury is observational and cannot establish causality. Observed associations may reflect confounding, reverse causation, exposure opportunity, or adaptive responses; causal models are therefore needed to define modifiable intervention targets [5,10,23,24,31,32]. Future research should prioritize causal frameworks to identify effective preventive strategies.

5.3. Device, firmware, algorithm and vendor drift

Technological changes may influence longitudinal measurements independently of athlete performance. Device interchangeability, algorithm updates, missingness, and incorrect configuration can alter the meaning of longitudinal data, potentially distorting longitudinal trends or the estimated effect of wearable-guided interventions [3,9,16,22,28-30]. Consistent hardware, software, and data-processing procedures are therefore essential.

5.4. Missing data, adherence and data quality

Missing data, inconsistent device use, and poor adherence reduce the quality of wearable datasets and may bias injury-risk estimates [3,16,28]. Standardized quality-control procedures and transparent reporting of missing data should therefore accompany wearable monitoring studies.

5.5. Generalizability, representativeness and equity

Current evidence is disproportionately derived from male, elite, football-based, and single-centre cohorts, limiting transportability across sex, age, competition level, and sport [2,13,26-28]. More diverse and multicentre studies are needed to improve external validity.

5.6. Human factors, workflow integration and alert burden

Successful implementation depends on how monitoring data are incorporated into everyday practice. Wearable systems should support rather than replace multidisciplinary judgment, with explicit governance for consent, access, data ownership, alert escalation, and accountability [6,16,36]. Clear workflows and effective communication are essential for translating monitoring into preventive action.

5.7. Privacy, athlete autonomy, data ownership and governance

The widespread use of wearable technologies raises important ethical and governance challenges. Monitoring programmes should ensure informed consent, protect athlete privacy, clearly define data ownership and access rights, and establish transparent governance procedures to promote responsible and trustworthy use of wearable-derived data [6,16,36].

6. Research priorities and future directions

6.1. A phased translational research agenda

Future research should focus less on developing new wearable devices and more on verifying whether existing technologies can meaningfully support injury prevention in everyday practice. This requires a stepwise approach—from validating measurements, through confirming clinically relevant associations and prediction models, to evaluating whether wearable-guided interventions reduce injury incidence in real training environments [6,12,13]. Such an approach is consistent with the Translating Research into Injury Prevention Practice (TRIPP) framework, which emphasizes that successful injury prevention depends not only on scientific evidence but also on its effective implementation in sport.

6.2. Multicentre prospective cohorts and harmonized data standards

To move from athlete monitoring to effective injury prevention, future studies must generate evidence that is reliable, reproducible, and applicable across different sports and populations. This requires multicentre prospective cohort studies conducted using standardized definitions of injury, athlete exposure, workload metrics, and outcome reporting, enabling meaningful comparisons between studies and more robust evidence synthesis [14]. Harmonized data collection would also facilitate external validation of wearable-based prediction models and improve the overall quality and clinical relevance of the available evidence [13]. Ultimately, greater methodological consistency will support the translation of wearable technologies from monitoring tools into effective components of injury prevention strategies [2,14].

6.3. Methodological standards for prognostic modelling and validation

As larger and more standardized datasets become available, the priority should shift from developing increasingly complex algorithms to building prognostic models that are transparent, reliable, and clinically useful. This requires large prospective datasets, clinically meaningful predictors, and rigorous validation to ensure that model performance can be reproduced in independent athlete populations [12,13]. Prediction models should also be reported according to established methodological standards, such as the TRIPOD guidelines, to improve transparency, reproducibility, and facilitate independent evaluation before they are implemented in practice [15].

6.4. Pragmatic trials of prespecified wearable-guided interventions

The real value of wearable technologies will be determined not by how much data they collect, but by whether they help reduce sports injuries in everyday practice. Future research should therefore focus on studies in which coaches or clinicians follow predefined actions based on wearable data, such as adjusting training load, modifying recovery plans, or changing exercise programmes [6,13]. This approach would make it possible to assess whether decisions supported by wearable technologies actually reduce injury incidence and severity under real training conditions. Current evidence suggests that the effectiveness of such interventions depends not only on the technology itself, but also on how consistently the recommendations are followed and how well the collected data are interpreted [16].

6.5. Co-designed, human-centred decision support

Wearable technologies should support decision-making rather than replace it. Future systems should be developed together with coaches, clinicians, and athletes to ensure that the information they provide is relevant, easy to understand, and practical in everyday training. Decision-support tools should present clear recommendations instead of large amounts of raw data, allowing users to make informed decisions without increasing their workload [17,18]. A human-centred approach may improve technology acceptance, encourage long-term use, and increase the likelihood that wearable-derived information will be translated into effective injury prevention strategies.

6.6. Open standards, reproducibility and post-deployment monitoring

The successful implementation of wearable technologies does not end when a prediction model is developed or introduced into practice. Models should be transparently reported, regularly evaluated, and continuously monitored to ensure that their performance remains reliable as training environments, athlete characteristics, and technologies evolve [15,19]. Whenever possible, researchers should promote reproducibility by clearly describing analytical methods and encouraging the use of shared reporting standards. Continuous post-deployment evaluation will help identify performance changes over time and ensure that wearable-based decision-support systems remain safe, accurate, and clinically relevant.
In summary:

- Future research should prioritize the quality of evidence rather than the quantity of wearable-derived data.
- Standardized methodologies, transparent reporting, and rigorous validation are essential to ensure that findings can be reproduced and applied across different sporting settings.
- The real value of wearable technologies should be assessed by their ability to support better decisions and contribute to measurable reductions in sports injuries.
- Achieving this goal will require close collaboration between researchers, clinicians, coaches, and athletes throughout both the development and implementation of wearable-based solutions.

7. Implications for current practice

7.1. Appropriate current uses of wearable technology

When used appropriately, wearable technologies can support injury prevention by:

- **Monitoring changes in training load over time**, allowing coaches to identify unusually rapid increases or decreases in workload that may require adjustments to training or recovery programmes [1,11,23,24].
- **Detecting early signs of fatigue or inadequate recovery** by combining workload measures with physiological indicators and athlete-reported outcomes, enabling timely

modifications before excessive overload develops [1,7,21].

- **Supporting individualized training programmes**, as athletes often respond differently to similar workloads. Wearable technologies help identify these individual responses and facilitate personalized progression rather than relying on universal workload thresholds [7,10,23].
- **Monitoring movement quality and biomechanics**, particularly during running and sport-specific activities, which may help identify changes associated with fatigue, altered movement patterns or increased mechanical stress requiring further clinical assessment [3,9,29].
- **Improving communication and shared decision-making** within the multidisciplinary performance team by providing objective information that complements clinical examination, coaching experience and athlete feedback [1,2].

At present, the greatest contribution of wearable technologies to injury prevention lies in supporting earlier, more individualized, and better-informed decision-making rather than in directly predicting injuries.

7.2. Uses not yet supported by sufficient evidence

Despite their growing popularity, some applications of wearable technologies are not yet sufficiently supported by scientific evidence. Likewise, no single workload metric or physiological parameter can accurately determine injury risk, as injuries result from the interaction of multiple factors that differ between athletes [10,23,31]. Although machine-learning models show promise, most have not been externally validated or tested in real-world intervention studies, limiting their current clinical use [13,19]. At present, wearable technologies should therefore complement professional judgement rather than replace it.

7.3. Minimum safeguards for implementation

To ensure that wearable technologies are used safely and effectively, several basic principles should be followed:

- Use validated devices and understand what each measured variable represents, as not every metric reflects injury risk [3,21,22].
- Interpret wearable data together with clinical assessment, athlete feedback, and

training context, rather than relying on a single parameter or algorithm [1,11,31].

- Define in advance how wearable data will influence training decisions, ensuring that responses are consistent and evidence-based [6,13].
- Regularly verify data quality and educate users about the capabilities and limitations of wearable technologies, as appropriate interpretation is essential for their effective use [17,18].

Following these principles can improve the practical value of wearable technologies while reducing the risk of inappropriate decisions based on isolated or misinterpreted data.

8. Limitations of this review

This narrative review should be interpreted in light of several limitations. By design, it does not follow the methodology of a systematic review or meta-analysis and therefore may not have captured all relevant publications on wearable technology and sports injury prevention [20]. The available evidence is also highly heterogeneous, reflecting differences in wearable devices, monitored variables, study populations, injury definitions, and outcome measures, which limits direct comparisons across studies [2,3]. Furthermore, much of the current literature focuses on measurement accuracy and injury prediction, whereas relatively few studies have evaluated whether wearable-guided interventions actually reduce injury incidence in real-world sports settings [13]. As wearable technologies and data-driven approaches continue to evolve rapidly, the conclusions presented in this review should be interpreted within the context of the currently available evidence.

9. Conclusions

Wearable technologies have the potential to become an important component of sports injury prevention, but the current evidence suggests that their role is supportive rather than independent. Their greatest contribution lies in helping practitioners recognize meaningful changes, individualize training, and make better-informed decisions before injuries occur. As evidence continues to grow, the focus should shift from developing new devices to demonstrating that wearable-guided strategies lead to measurable improvements in athlete health and injury outcomes. Ultimately, wearable technologies should be evaluated not by the amount of data they generate, but by their ability to contribute to safer and more effective sports participation.

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