



Wearable Technology for Injury Risk Screening in Sports: A Mini-Review

Calk P*

Researcher Scholar, USA

***Corresponding author:** Patti Calk, Researcher Scholar, USA

Editorial

Volume 9 Issue 2

Received Date: April 04, 2026

Published Date: April 26, 2026

Abstract

The translation of wearable sensor data into actionable clinical insights represents a pivotal frontier in sports medicine. This mini review synthesizes current evidence on the use of inertial measurement units (IMUs), global navigation satellite systems (GNSS), and other wearable biosensors for the purpose of injury risk screening. We examine the underlying premise that biomechanical and physiological variables—such as joint kinematics, ground reaction force surrogates, and heart rate variability—can serve as digital biomarkers of impending tissue overload or neuromuscular dysfunction. Recent investigations have moved beyond simple workload monitoring to incorporate machine learning algorithms that integrate multi-modal sensor data, potentially improving predictive accuracy. However, the field is characterized by considerable heterogeneity in sensor placement, metric derivation, and outcome definition. The gap between identifying correlative risk factors in retrospective datasets and deploying prospective, individualized screening protocols remains substantial. We contend that the current enthusiasm for wearables must be tempered by a rigorous appraisal of their predictive validity and clinical utility. Key challenges include establishing normative data across populations, accounting for the influence of contextual factors like playing surface and psychological state, and validating algorithms across diverse sporting environments. While wearable technology offers unprecedented opportunities for continuous, ecologically valid assessment, its role in injury prevention will ultimately depend on the development of transparent, validated models that are interpretable to clinicians and athletes alike.

Keywords: Wearable Sensors; Injury Prediction; Biomechanics; Machine Learning; Sports Medicine; Athlete Monitoring

Abbreviations

Imus: Inertial Measurement Units; GNSS: Global Navigation Satellite Systems; ACWR: Acute Chronic Workload Ratio; HR: Heart Rate; HRV: Heart Rate Variability; RMSSD: Root Mean Square of Successive Differences; ML: Machine Learning; ACL: Anterior Cruciate Ligament.

Introduction

The prevention of sports-related injuries has long been a cornerstone of athletic performance optimization and

public health. Traditional screening methods, ranging from preseason functional movement assessments to isokinetic dynamometry, have demonstrated limited capacity to accurately identify individuals at elevated risk. These methods are often constrained by their laboratory-based nature, providing a single snapshot of an athlete's capacity that may not reflect the dynamic, fatigued, and unpredictable conditions of actual sport participation. The emergence of wearable technology has shifted the paradigm toward continuous, real-world monitoring. Devices such as IMUs, GNSS, and heart rate monitors can now capture vast streams of data on an athlete's external workload and internal

physiological response during both training and competition. This wealth of data has ignited hope that algorithms can be developed to predict injury with sufficient accuracy to enable meaningful intervention.

The fundamental hypothesis driving this field is deceptively simple: injuries are not random events but rather the culmination of a cascade of microtrauma or a failure of neuromuscular control under load [1].

Wearable sensors can potentially detect the subtle changes in movement patterns or physiological state that precede this failure. For example, a progressive loss of knee flexion during landing, an increase in step variability, or an altered heart rate recovery profile could each signify an elevated risk state. This review is predicated on the belief that while the technological capacity for data collection has outpaced the scientific understanding of how to interpret these data, significant progress has been made in recent years. We aim to synthesize the current evidence across key sensor modalities, methodological approaches, and analytical frameworks, while critically evaluating the limitations that currently prevent the widespread implementation of wearable-based injury screening as a standard of care.

Sensor Modalities and Derived Metrics for Injury Screening

The landscape of wearable technology for injury risk assessment is diverse, with different sensor types offering distinct insights. The most prevalent are IMUs, which incorporate accelerometers, gyroscopes, and magnetometers. These are typically worn on the lumbar spine, shanks, or upper arms. From raw tri-axial acceleration and angular velocity data, a host of metrics are derived. These include Player Load, a vector magnitude of acceleration that estimates mechanical work, and more complex variables like peak angular velocity, stride length, and ground contact time [2]. GNSS technology, often combined with IMUs in a single unit, provides information on total distance, high-speed running distance, and acceleration/deceleration counts. The emphasis here is on external load—the physical work performed by the athlete. A well-documented relationship exists between spikes in these external load metrics and subsequent non-contact soft tissue injuries, particularly in field sports like soccer and Australian football [3,4]. The “acute: chronic workload ratio” (ACWR), which compares recent load to a rolling average of past load, emerged as a practical, if controversial, metric from this data stream.

Complementing external load, physiological sensors are gaining traction. Heart rate (HR) monitors, whether chest-strap or optical, provide data on internal load. Metrics like heart rate variability (HRV), particularly the root mean square

of successive differences (RMSSD), are used as indicators of autonomic nervous system balance. A depressed HRV is often interpreted as a sign of incomplete recovery or heightened stress, potentially predisposing an athlete to injury [5]. More recent developments include sweat sensors and temperature probes, though their application in injury screening remains nascent. The synergy arises when combining these streams; for instance, an athlete’s cardiovascular response (internal load) relative to their mechanical work (external load) can provide a more comprehensive picture of training stress than either metric in isolation. This notion of a “training stress balance” is conceptually appealing but methodologically challenging to operationalize.

Computational Methods and the Machine Learning Paradigm

The sheer volume and complexity of data generated by wearables have necessitated advanced computational approaches. Simple univariate threshold-based screening—e.g., “if Player Load exceeds X, the athlete is at risk”—has proven inadequate due to the highly individual nature of injury etiology. This has catalysed the application of machine learning (ML) and deep learning models. These algorithms excel at detecting non-linear interactions between numerous variables, potentially uncovering patterns that elude traditional statistical methods. Recent studies have employed random forests, gradient boosting, and support vector machines to classify athletes as “high-risk” or “low risk” based on a feature set derived from wearable data over a preceding period [6,7].

A notable paradigm shift is the move from retrospective injury prediction to prospective, individualized monitoring. Many early ML models, while achieving high accuracy on training datasets, suffered from overfitting and a lack of generalizability. The development of anomaly detection algorithms offers a different approach. Instead of a binary “will injure/won’t injure” prediction, these models establish a personalized baseline of movement or performance metrics for each athlete. Any significant deviation from this baseline is flagged as a potential risk event, prompting clinical evaluation. This aligns more closely with the clinician’s need for decision support rather than a deterministic prediction. For instance, a recurrent neural network can be trained on a continuous stream of IMU data from a single athlete to learn their unique stride-to-stride variability. A subsequent increase in variability beyond a statistically derived control limit could trigger an alert. This approach, focusing on intra-individual changes, addresses the critical challenge of inter-individual variability that plagues group-based models. However, the clinical utility of such alerts remains contingent on defining appropriate action thresholds and ensuring that false positives do not desensitize the clinical team.

Case Studies and Clinical Application: The ACL and Hamstring Injury Context

To ground the discussion, it is instructive to consider specific injury types. Anterior cruciate ligament (ACL) injuries and hamstring strains are among the most prevalent and debilitating non-contact injuries in sport, and consequently, they are a primary target for wearable-based screening. The biomechanical signature of ACL injury risk often involves increased knee valgus and decreased knee flexion during landing and cutting maneuvers. While these are typically assessed in a gait lab, wearable IMUs have been used to estimate these parameters in the field. Studies have demonstrated that variables like the acceleration at initial contact and the rate of change of the knee angle, as estimated from shank and thigh-mounted sensors, can discriminate between individuals with high and low risk profiles during drop jumps. The challenge, however, is in capturing the specific, infrequent event of a high-risk maneuver in an uncontrolled environment.

For hamstring injuries, the narrative has historically focused on eccentric hamstring strength and biceps femoris architecture. Wearable technology has shifted the focus to the external load that precipitates injury. High-speed running and the number of “sprints” (>80% of max speed) have been consistently linked to hamstring injury risk, with a particular emphasis on the ACWR for these high-intensity actions. More sophisticated analyses are now exploring the timing of these efforts, suggesting that the distribution of high-speed running, not just the cumulative volume, is critical. For example, concentrated bursts of sprinting are more provocative than the same volume distributed over a longer period. The integration of these external load metrics with internal load data (like HRV) may offer a more nuanced understanding. A decline in HRV coupled with a high “sprint load” could represent the window of heightened vulnerability.

Despite these promising avenues, prospective studies that demonstrate that modifying an athlete’s training load based on these wearable metrics reduces the incidence of hamstring or ACL injuries are surprisingly scarce, a point we will return to.

Limitations and Research Gaps

Despite the optimism, the wearable technology field is fraught with critical limitations that must be acknowledged. Chief among these is the “signal vs. noise” problem. The human body is a complex, adaptive system; variability is inherent. Distinguishing a pathological change in a metric from normal physiological fluctuation or sensor artefact is a formidable challenge. Many published studies suffer from

small sample sizes, often confined to a single team or season, which severely limits the generalizability of findings. The gold standard for evaluating screening tests, the prospective cohort study with a clear intervention, is resource-intensive and rarely conducted.

Furthermore, there is a significant lack of standardization in sensor placement, data processing pipelines, and the definitions of variables. This makes direct comparison between studies difficult and impedes the creation of robust, open-source benchmarking datasets. The validation of many derived metrics against “ground truth” laboratory equipment (e.g., motion capture systems, force plates) is often inadequate, raising questions about the accuracy of the field-based estimates. Another major gap is the integration of psychological and contextual factors. Injury is a multifactorial event; workload and movement patterns are merely components. An athlete’s sleep quality, psychosocial stress, nutritional status, and even the playing surface all contribute to injury risk. Wearable data alone cannot capture this full picture. The development of integrated models that combine biomechanical data with patient-reported outcome measures and coaching staff observations is an essential, yet largely unexplored, area of research.

Conclusion

Wearable technology has undeniably expanded the horizon of what is possible in injury risk screening, transitioning the assessment from the laboratory to the training ground and competitive arena. The data generated are rich and continuous, providing a window into the athlete’s dynamic state. We have seen a clear evolution from simple workload monitoring to more sophisticated algorithms that attempt to integrate multiple data streams and model intra-individual variations. The use of machine learning is beginning to address the complexity of the problem, offering the promise of personalized risk alerts. However, the current body of evidence is characterized by numerous methodological shortcomings that undermine the translation of these technological advances into clinical practice. The field must now pivot from a phase of data exploration to one of rigorous validation.

The critical path forward involves large-scale, multi-centre prospective studies that are designed with clinical implementation in mind. Researchers must establish common data standards and collaborate to build public repositories that can be used to test and benchmark algorithms. The development of “explainable AI” is paramount; clinicians will not trust a “black box” that issues a risk score without a clear rationale. Ultimately, the value of a screening tool is not its predictive accuracy alone, but its ability to guide effective, low-cost interventions. The most pressing question

for the next decade is not “Can we predict injury?” but rather “Can we use these data to prevent it?” This will require a concerted effort from engineers, data scientists, sports medicine clinicians, and the athletes themselves to ensure that this powerful technology is used wisely and effectively.

References

1. Bittencourt NFN, Meeuwisse WH, Mendonça LD, Nettel-Aguirre A, Ocarino JM, et al. (2016) Complex systems approach for sports injuries: moving from risk factor identification to injury pattern recognition—narrative review and new concept. *British Journal of Sports Medicine* 50(21): 1309-1314.
2. Chambers R, Gabbett TJ, Cole MH, Beard A (2015) The use of wearable microsenors to quantify sport-specific movements. *Sports Medicine* 45(7): 1065-1081.
3. Gabbett TJ (2016) The training—injury prevention paradox: should athletes be training smarter and harder? *British Journal of Sports Medicine* 50(5): 273-280.
4. Hulin BT, Gabbett TJ, Blanch P, Chapman P, Bailey D, et al. (2014) Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *British Journal of Sports Medicine* 48(8): 708-712.
5. Flatt AA, Esco MR (2015) Heart rate variability stabilization in athletes: a review of the literature. *Sports Medicine* 45(5): 683-698.
6. Rossi A, Pappalardo L, Cintia P, Iaia FM, Fernández J, et al. (2019) Effective injury forecasting in soccer with a machine learning model based on GPS and IMU data. *Scientific Reports* 9(1): 1-10.
7. Carey DL, Ong K, Whiteley R (2018) Predicting hamstring strain injury in elite athletes using a machine learning approach. *Journal of Science and Medicine in Sport* 21(11): 1100-1105.

YOUR RESEARCH DESERVES GLOBAL VISIBILITY

• Publish • Discover • Share • Connect

MEDICAL	CLINICAL	LIFESCIENCES	PHARMA
90+ OPEN ACCESS JOURNALS		400+ RESEARCH TOPICS	

SUBMIT YOUR RESEARCH

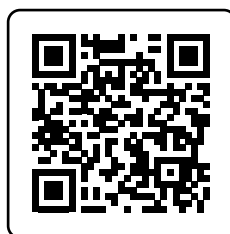
Submit your manuscript through our online submission system.

REPRINTS

If you require a reprint of any article, please contact us.
info@medwinpublishers.com

BECOME A REVIEWER

Share your expertise and contribute to scholarly publishing.



SCAN TO EXPLORE MEDWIN JOURNALS

• Journals • Submit Manuscript • Reviewer Program • Article Tracking

Our Journals indexed in



This article published by **Medwin Publishers**, 28475 Witherspoon Dr, Novi, MI 48377, United States, +1-248-247-6042, WhatsApp +1 (248) 275-1133, info@medwinpublishers.com

© 2026, by the Authors. The articles published from this journal are distributed to the public under “**Creative Commons Attribution License**” (<https://creativecommons.org/licenses/by/4.0/>). Therefore, upon proper citation of the original work, all the articles can be used without any restriction or can be distributed in any medium in any form.