Wearable sensors and machine learning in sports biomechanics

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EDITORIAL

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ABSTRACT

A central challenge in sports biomechanics has long been to translate precise laboratory-based measurements into meaningful insights for real-world sport performance and injury prevention. Wearable sensors, particularly inertial measurement units, combined with machine learning methods, are central to this transition because they enable the estimation of biomechanical variables outside controlled laboratory environments. This Editorial introduces the Special Issue “Wearable Sensors and Machine Learning in Sports Biomechanics”, which brings together four contributions illustrating the current state and future potential of this rapidly developing field. The articles address key methodological and applied questions: the quantification of whole-body technique in soccer penalty kicks using IMU-based principal component analysis; the detection of psychological and physiological processes through multimodal sensor data and gamification; the estimation of running kinetics in outdoor environments using convolutional neural networks; and a structured overview of current research on field-based biomechanical load assessment across diverse sports. Collectively, these contributions demonstrate how wearable sensors and machine learning are becoming important methodological components for studying movement, biomechanical load, and performance in ecologically valid settings. While highlighting substantial advances, the Special Issue also identifies ongoing challenges, including methodological heterogeneity, limited external validation, and the need for explainable and physics-informed approaches. Ultimately, wearable sensors and machine learning can support a new generation of biomechanical tools, but their impact will depend on generating interpretable, valid, and actionable insights in real-world sporting environments.

Keywords

artificial intelligence, field-based biomechanics, current research trends, future directions

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Motivation

Sports biomechanics is currently undergoing a substantial transformation in how human movement is analyzed, interpreted, and applied in practice (Liu et al., 2026). Biomechanical analysis of human movement has conventionally been conducted in laboratory settings, utilizing sophisticated yet restrictive equipment such as marker-based optical motion capture systems and force plates (B. M. Nigg & Herzog, 2007). Although these methods provide high temporal and spatial precision, their use in training and competition environments is limited by high costs, time-intensive setup procedures, and restricted ecological validity (Dindorf et al., 2025; Mundt, 2025). The long-standing goal of transferring biomechanical analysis from the laboratory to the field is therefore becoming increasingly attainable (Camomilla et al., 2018; Cronin, 2021; Dorschky et al., 2023)

The relevance of this development lies in the growing need to provide athletes, coaches, clinicians, and practitioners with actionable biomechanical information in real-world settings (Camomilla et al., 2018; Verheul et al., 2020). Wearable technologies, particularly inertial measurement units (IMUs) have become central to this transition (Dorschky et al., 2023; Liu et al., 2026). These sensors are portable, lightweight, comparatively inexpensive, and allow largely unobtrusive monitoring during dynamic, sport-specific movements (Stetter & Stein, 2024). Typical raw signals obtained from these sensors include acceleration and angular velocity. However, these signals are inherently difficult to interpret in isolation and do not directly provide comprehensive kinetic parameters, such as ground reaction forces, joint moments, or joint contact forces, which are achievable through established laboratory-based measurement and modeling systems (Hafer et al., 2023).

Machine learning (ML) offers a promising approach to bridging this gap (Mundt, 2025). ML methods are well suited to identifying complex, non-linear relationships in high-dimensional sensor data that are difficult to capture using conventional statistical approaches (Stetter & Stein, 2024; Xiang et al., 2022). By training ML models on synchronized datasets that combine wearable sensor data with laboratory-based reference data, researchers can predict biomechanical variables such as joint angles, external forces, joint moments and joint contact forces from wearable signals. This opens new possibilities for lab-independent biomechanical analysis and for assessing movement mechanics under more natural and sport-specific conditions (Dorschky et al., 2023; Liu et al., 2026).

Research in this field is continually advancing beyond basic prediction and recognition methods, moving toward more sophisticated deep learning architectures such as convolutional neural networks (CNNs) and long short-term memory networks (Souaifi et al., 2025; Xiang et al., 2022). These methods are increasingly being applied in areas such as injury prevention, performance analysis, technique assessment, and movement recognition. For example, ML-based approaches may help identify fatigue-related changes in running or movement patterns that are relevant to injury risk. Similarly, automated technique assessment systems may support coaches and athletes by providing objective feedback during training and competition (Dorschky et al., 2023; Souaifi et al., 2025).

Despite these substantial advances, several significant challenges remain concerning practical application. The field is characterized by considerable methodological heterogeneity, which makes it difficult to compare findings across studies and to establish generalizable conclusions (Liu et al., 2026). Many ML applications in sports biomechanics are still exploratory, and model performance is often constrained by small, homogeneous datasets and limited external validation (Dindorf et al., 2025; Krondorfer et al., 2026). In addition, the “black-box” nature of many ML approaches raises concerns regarding interpretability, transparency, and trust, particularly when model outputs are used to inform clinical, coaching, or training decisions. Addressing these challenges through explainable AI, robust validation procedures, and physics-informed models that integrate biomechanical principles into the learning process represents an important frontier for future research (Dindorf et al., 2025; Krondorfer et al., 2026; Xiang et al., 2025).

The special issue, “Wearable sensors and machine learning in sports biomechanics”, follows the highlighted research directions outlined by C. Nigg et al. (2022). It brings together four contributions that illustrate the current state and future potential of this rapidly developing field. The articles address key methodological and applied questions. These include the quantification of whole-body technique in soccer (Debertin et al., 2026), the detection of implicit psychological and physiological processes using multimodal sensor data (Lennartz et al., 2026), the estimation of running kinetics in outdoor environments (Höschler et al., 2026), and the broader state of research on field-based biomechanical load assessment in sport (Stetter et al., 2026).

Highlights of the special issue articles

The study by Debertin et al. (2026) addresses the quantification of penalty-kick technique in soccer via wearable sensor data and principal component analysis (PCA). Penalty kicks are highly relevant performance situations in soccer, yet their biomechanical analysis remains challenging because successful execution depends on coordinated whole-body movement rather than isolated kinematic variables. An IMU-based PCA framework was developed to identify interpretable “technique components”, facilitating practical movement strategy assessment. Sixteen male amateur soccer players executed penalty kicks under instructed technique variations and self-selected shot-placement conditions, with whole-body kinematics captured using an Xsens IMU system. PCA conducted on time-normalized and mass-weighted segment data identified components representing horizontal, vertical, and lateral body motion; upper-body rotation; leg-swing strategy; arm swing; and head orientation, enabling systematic exploration of technique variation with respect to shot placement. The findings indicate, for example, that shots toward upper goal zones were characterized by a lower vertical body position and stronger lateral lean toward the standing leg. This article demonstrates how wearable sensors can be combined with dimensionality-reduction methods to generate interpretable, practice-oriented measures of complex sport technique. It also highlights the value of translating high-dimensional biomechanical data into concepts that are meaningful for coaches and athletes.

The study by Lennartz et al. (2026) broadens research on wearable sensing and ML by exploring how gamification influences biosignals, performance, and motivation in soccer, moving beyond traditional biomechanical metrics. Motivation is a central determinant of athletic behavior and performance, but it is still commonly assessed through self-report questionnaires, which provide only limited insight into continuous and implicit processes during performance. In this study, gamification elements grounded in self-determination theory were used to influence motivational states during a soccer passing drill in an immersive environment. Forty-two participants completed both gamified and non-gamified scenarios while performance data, cardiovascular signals, and eye-tracking metrics were collected. The authors combined conventional statistical analysis with ML classification to examine whether biosignals and performance measures differed between conditions. Although self-report questionnaires and performance metrics did not reveal significant differences, ML models were able to distinguish between the two scenarios based primarily on eye-tracking features. The best-performing k-nearest neighbor classifier achieved a macro F1-score of 82.75%, with blink behavior and pupil dynamics emerging as important contributors. This article illustrates the potential of multimodal wearable and sensor-based data to uncover implicit psychological and physiological processes that may remain hidden when relying only on questionnaires or overt performance outcomes. It also broadens the conceptual scope of sports biomechanics by linking movement-related assessment with cognition, motivation, and visual attention.

The study by Höschler et al. (2026) addresses a central question in running biomechanics: how running speed influences lower-limb joint kinetics and ground reaction forces under real-world outdoor conditions. While speed-dependent changes in running kinetics have been extensively studied in laboratory environments, field-based evidence remains limited. The authors used three IMUs placed on the foot, shank, and pelvis in combination with a CNN trained to estimate ipsilateral ground reaction forces and lower-limb joint moments. After validation on an independent dataset, the CNN was applied to twenty-nine recreational runners performing an incremental running-speed protocol on a 400 m outdoor track. Statistical parametric mapping was used to examine speed-related differences across the stance phase. The results showed that running speed affected all kinetic parameters during most of stance phase. Ground reaction forces as well as ankle and hip moments increased across speed increments, whereas knee moments were largely unaffected by speed increases beyond 10 km/h. These findings suggest that reducing running speed may be particularly relevant for mitigating ankle- and hip-related loading. Importantly, the observed field-based patterns were consistent with findings from laboratory studies, supporting the feasibility of IMU- and ML-based approaches for assessing running biomechanics in ecological conditions. The study therefore provides an important example of how laboratory-derived biomechanical knowledge can be transferred to, and evaluated in, real-world sport settings.

The study by Stetter et al. (2026) provides a structured overview and broader perspective on the use of wearable sensors and ML for field-based biomechanical load assessment in sports. The assessment and management of biomechanical load, including ground reaction forces, joint moments, and related movement execution metrics, is highly relevant for both performance development and injury prevention. The authors systematically reviewed current research on wearable sensors combined with ML for assessing biomechanical load outside the laboratory. Searches in PubMed and SPORTDiscus identified 4,546 articles, of which 42 met the eligibility criteria. Data were extracted on participant characteristics, sports and movement tasks, wearable sensor types and placement, ML methods, model inputs and outputs, validation strategies, and key findings. Running was the most frequently studied sport, although nine other sports were also represented. Artificial neural networks and linear regression were among the most commonly applied ML methods. Biomechanical load was most often assessed using ground reaction force metrics, followed by movement execution and joint moment metrics. Given the predominant focus on running, the review identifies a need to extend investigations to sports with complex, multidirectional, and upper-body movements and to improve assessment of upper-extremity loading. Although ground reaction force is still the most commonly predicted metric, research is shifting toward more specific measures, including joint moments and tissue-level stresses. This overview offers a valuable foundation for interpreting current progress and setting future directions for the field.

Summary and conclusion

Taken together, the four articles in this special issue show that wearable sensors and ML are no longer merely technological additions to sports biomechanics. Rather, they are becoming central methodological components for studying movement, biomechanical load, technique, and performance in ecologically valid settings (Dorschky et al., 2023; Souaifi et al., 2025). The included contributions also demonstrate the breadth of this development: from interpretable technique components in soccer penalty kicks, to multimodal assessment of motivational states, to CNN-based estimation of outdoor running kinetics, and finally to a structured synthesis of the current evidence base for field-based biomechanical load assessment.

Collectively, the articles highlight how wearable sensors and ML can contribute to the transition from laboratory-based research toward field-based applications. They show that ML-based approaches can support the estimation of biomechanical variables in outdoor settings (Debertin et al., 2026; Höschler et al., 2026; Stetter et al., 2026), but also that multimodal sensor data may reveal implicit psychological and physiological processes, such as changes in visual attention, that are not necessarily captured by questionnaires or conventional performance metrics alone (Lennartz et al., 2026). At the same time, the special issue makes clear that the field is still in a phase of methodological consolidation. Future research could prioritize larger and more diverse datasets, external testing across populations and environments, and closer integration of biomechanical theory with data-driven modelling (Krondorfer et al., 2026; Mundt, 2025). Explainable and physics-informed ML approaches may be particularly valuable for ensuring that ML model outputs are not only accurate, but also interpretable, biologically plausible, and trustworthy for practitioners (Dindorf et al., 2025; Stetter & Stein, 2024; Xiang et al., 2025).

In conclusion, wearable sensors and ML offer substantial potential for advancing sports biomechanics by extending biomechanical analysis beyond the laboratory and into real-world sport settings. Their greatest value lies not in replacing established laboratory-based methods, but in complementing them and enabling new forms of mobile, individualized, and context-sensitive assessment. By fostering interdisciplinary collaboration, rigorous validation, and meaningful translation into practice, the field can move toward a new generation of biomechanical tools that support performance enhancement, injury prevention, and long-term athlete health.

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