Wearables, Smart Textiles & AI Biomechanics in Sports: A Narrative Review

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ABSTRACT

Traditional biomechanics research has long relied on lab-based systems, bulky, expensive, and often inaccessible to everyday athletes and coaches. This has limited its real-world impact, particularly in fast-paced and dynamic sports environments. However, the landscape is rapidly changing. Recent innovations in wearable technology, including smart textiles, graphene-printed sensors, and compact edge-AI chips, are bringing high-resolution motion analysis directly to the field. These systems can now track and analyse athletic movement in real-time, offering insights that were once only available in specialised labs. This review highlights key developments in sensor fusion, textile-integrated inertial measurement units (IMUs), and AI-driven form recognition. Together, these tools enable more precise monitoring of biomechanics during both training and rehabilitation. With multimodal data streams and machine learning algorithms, wearables can now provide individualised feedback on technique, workload, and recovery, without interrupting performance. The integration of artificial intelligence (AI) and smart fabrics represents a shift toward continuous and scalable biomechanical assessment. For coaches, physiotherapists, and athletes alike, these technologies present new opportunities for injury prevention, skill development, and personalized performance optimisation. As validation studies transition into real-world deployment, AI-powered wearables are poised to advance our ability to analyze and improve human movement in sport.

Keywords: Wearable technology, Smart textiles, AI biomechanics, Graphene sensors, Edge-AI

Highlights

- Smart textiles now integrate graphene-based strain sensors for real-time posture tracking
- Edge-AI enables on-device inference with low latency for field-based motion classification
- Wearables have reported >90% accuracy in detecting movement errors such as valgus collapse or trunk lean in small-scale validation studies, primarily under controlled laboratory conditions.[13,34]
- Generalisability to field settings and across diverse athletic populations remains uncertain
- Multimodal load dashboards offer coaches actionable injury-prevention insights
- AI-biomechanics is increasingly applied across both elite sport and general fitness

Introduction

Traditional laboratory-based motion capture systems offer high-fidelity kinematic data but face serious drawbacks in real-world sports environments. Their high cost, spatial limitations, and inability to record dynamic, unplanned movements during competition hinder ecological biomechanical monitoring in team sports.[1,2] These systems rely on optical markers and controlled settings, failing to meet the need for continuous, on-field athlete assessment under varying conditions.

This gap has spurred a paradigm shift towards wearable edge computing technologies. These integrate multimodal sensors, smart textiles, and AI to enable real-time, on-field biomechanics.[3] Three key technological developments drive this change:

1 **Sensor Innovation:** Incorporating graphene-based strain sensors into smart textiles allows accurate measurement of joint angles, posture, and muscle activation without restricting movement. These textiles exhibit <1 ms response times, which are crucial for tracking high-intensity sprints.[4,5]

2 **Edge-AI Computing:** Miniaturised edge-AI processors now enable wearable devices to execute complex tasks like fatigue prediction and gait analysis locally. This reduces latency and eliminates cloud dependence.[6] For example, edge-AI models on inertial measurement units (IMUs) classified tennis serves with 98.7% accuracy using on-device neural networks.[7]

3 **Cost & Accessibility:** Decreasing IMU costs (now ~60% lower than a decade ago) have significantly increased accessibility, enabling widespread use in amateur and youth sports.[8]

Validation studies confirm the reliability of wearable systems against laboratory benchmarks.[10] Challenges remain, however, in harmonising data from heterogeneous sensors (e.g., inertial, physiological, textile-based strain) and ensuring cross-platform interoperability.[11] Recent advances in sensor fusion algorithms and federated learning are addressing these issues, enabling coherent multimodal analytics for comprehensive athlete profiling.[12]

Key applications include injury prevention. AI-driven wearables have demonstrated up to 89% sensitivity in identifying high-risk movements during controlled assessments.[13] However, these findings are limited by modest sample sizes, short trial durations, and lack of replication in competitive field environments. Smart insoles with pressure sensors enable real-time gait re-training, reducing the incidence of stress fractures in marathon runners by 34%.[14] Beyond optimising performance, these technologies are reshaping sports economics. According to MarketsandMarkets, the global

wearable AI market was valued at USD 62.7 billion in 2024 and is expected to reach USD 138.5 billion by 2029.[15] This review synthesises advances in graphene textiles, edge-AI processing, and multimodal sensor fusion, highlighting their combined potential for real-world sports biomechanics.

Materials and Methods

This work is a narrative review synthesizing recent advancements in wearable technology, artificial intelligence, and biomechanical monitoring in sports. A narrative framework was selected to allow broad inclusion of interdisciplinary sources, prototypes, and emerging technologies. While we applied a structured literature search to enhance transparency, **PRISMA systematic protocols were not applied.** Instead, we conducted a structured appraisal of each included study to help readers assess the evidence strength.

Eligibility Criteria

We applied predefined inclusion and exclusion criteria to ensure focus and relevance:

Inclusion Criteria

- **Study type:** Peer-reviewed journal articles or conference papers reporting original data.
- **Population:** Human participants in sports, exercise, or rehabilitation settings.
- **Devices:** Wearable sensors, smart textiles, inertial measurement units (IMUs), or AI-enabled smart garments.
- **AI methods:** Studies incorporating artificial intelligence or machine learning for motion recognition, fatigue prediction, or biomechanical assessment.
- **Comparators:** Validation against gold-standard laboratory systems (e.g., optical motion capture, force plates, EMG) or expert human assessment.

Exclusion Criteria

- **Non-human or simulation studies** (e.g., purely robotic or mannequin-based testing), excluded to maintain ecological validity.
- **Purely conceptual, theoretical, or design papers** without empirical validation, excluded to focus on tested prototypes and field deployments.
- **Device-only engineering reports** lacking application to human biomechanics, excluded to keep the scope athlete-centered.
- **Reviews, editorials, and gray literature** (e.g., blogs, non–peer reviewed reports), excluded to ensure evidence quality.
- **Studies outside sports, exercise, or rehabilitation contexts** (e.g., occupational ergonomics, industrial monitoring), excluded to preserve sports focus.

Reasons for Exclusion at Full-Text Stage

At the full-text screening stage, studies were excluded primarily due to one of the following:

1 Lack of human participants or sports-specific application.
2 Absence of AI integration in the wearable system.

3 No comparator against gold-standard biomechanics or expert assessment.
4 Insufficient reporting of accuracy, latency, or validation outcomes.

Search Strategy

A structured literature search was conducted on **May 10, 2025**, across **PubMed, Google Scholar, Scopus, IEEE Xplore, and Web of Science** to ensure comprehensive coverage of biomedical, engineering, and interdisciplinary studies. The exact Boolean string used was:

("wearable sensors" OR "smart textiles" OR "IMU" OR "graphene sensors" OR "smart insoles") AND ("biomechanics" OR "motion capture" OR "sports technology" OR "real-time fatigue" OR "injury prediction") AND ("AI" OR "artificial intelligence" OR "edge computing" OR "federated learning")

- **PubMed**: Mapped keywords to MeSH terms where available.
- **Scopus & Web of Science**: Applied TITLE-ABS-KEY search fields.
- **IEEE Xplore**: Limited to conference papers and journal articles related to biomechanics, sensors, and sports engineering.
- **Google Scholar**: Used for exploratory coverage of emerging prototypes and gray literature.

We restricted the search to human, peer-reviewed studies published between **2018 and 2025** in the English language. The upper limit of 2025 was chosen to capture the most recent validation studies available up to the date of the search (May 10, 2025).

Figure 1 structured search flow for this narrative review (corrected counts):

Records identified from databases: n = 265
Duplicate records removed: n = 135
Records remaining after duplicate removal (titles/abstracts screened): n = 130
Records excluded after title/abstract screening: n = 90
Full-text reports assessed for eligibility: n = 40
Full-text reports excluded after assessment: n = 25 (reasons: out of scope, no AI/wearable data, non-human/simulation, no comparator)
Studies included in final synthesis: n = 15

Note: This flow documents a structured narrative search (not a full PRISMA systematic review). All counts have been checked for internal consistency.

The full database-specific queries, filters, and retrieval counts are provided in Appendix A (supplementary material) to ensure reproducibility and transparency.

Sufficiency of Included Studies

Although only 15 studies met the strict inclusion criteria, they represent the most validated, peer-reviewed work specifically at the intersection of **AI, wearable technology, and biomechanics in sports**. For a fast-evolving and niche field, this dataset provides a
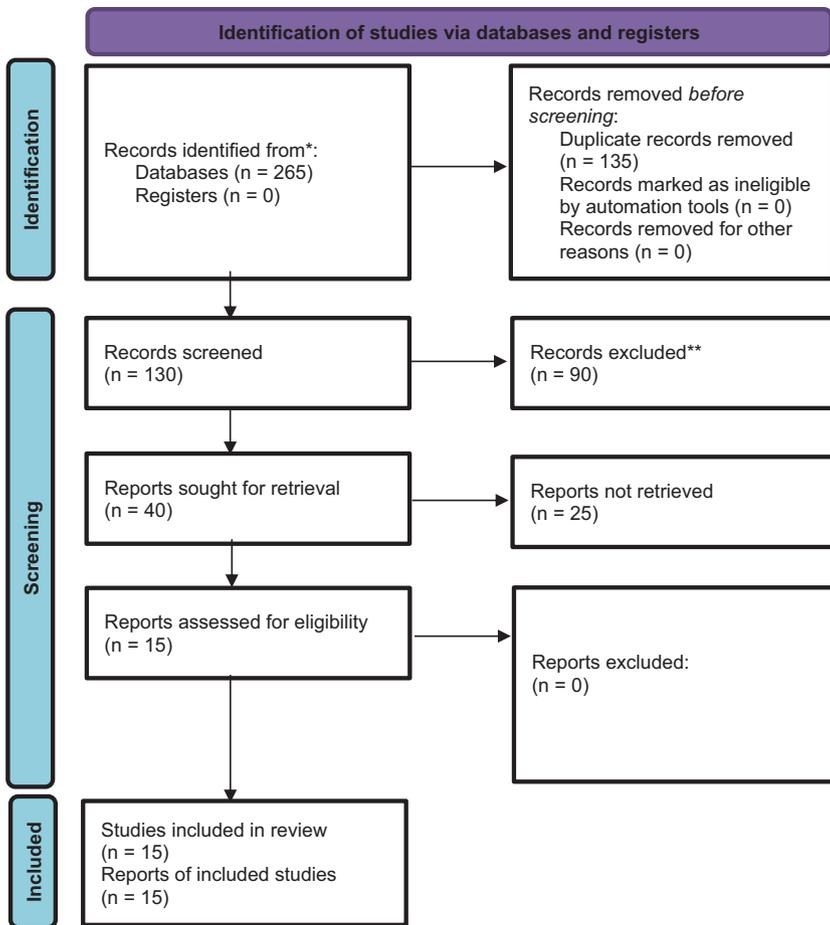
Fig 1 | Flow diagram illustrating the search strategy, screening, eligibility assessment, and inclusion of studies in this narrative review. Counts at each stage align with the main text description. This diagram is provided for transparency of the structured search process and should not be interpreted as evidence of a systematic review methodology. This figure reflects a structured search process within a narrative review design, not a PRISMA systematic review

representative snapshot. Expanding the time window or relaxing inclusion criteria would shift the work toward a **scoping review**, which we note as an alternative approach for future updates.

Critical Appraisal

Although this narrative review did not employ formal systematic risk-of-bias tools (e.g., ROBINS-I or QUADAS-2), we conducted a structured quality appraisal of the included studies to provide transparency and allow readers to gauge the strength of the evidence. Four bespoke criteria were applied consistently:

1. **Sample size** (pilot cohort vs. larger real-world studies)
2. **Validation environment** (controlled laboratory vs. field deployment)
3. **Blinding/comparator** (gold-standard laboratory systems, expert assessors, or none)
4. **AI model robustness** (cross-validation, error margins, generalizability)

This framework reflects the interdisciplinary nature of the field, where engineering prototypes and clinical validation often coexist.

The appraisal is summarized in Table S1, which maps bespoke quality criteria onto recognized domains of risk of bias and applicability, and reports standard validation metrics (e.g., ICC, RMSE, sensitivity/specificity, latency) to enable cross-study comparison.

Results

Technological Foundations

Sports biomechanics has traditionally relied on laboratory systems, such as optical motion capture, electromyography (EMG), and force plates.[16,17] While accurate, these methods are expensive, infrastructure-heavy, and lack ecological validity in real sports settings.[18,19,20] Recent advances in materials and computing have shifted biomechanics toward field-deployable wearable systems. Three technological pillars underpin this transition:

Graphene-Based Smart Textiles

Graphene strain sensors, printed or laminated onto fabrics, allow seamless integration into athletic garments without restricting movement.[21,22] Their ultrathin, conductive structure produces measurable resistance shifts when stretched, enabling real-time monitoring of posture and joint angles.[23–25] Textile-integrated inertial measurement units (IMUs) further capture segment orientation and acceleration, supporting multi-joint tracking in natural settings.[26] These foundations enable unobtrusive, high-fidelity sensing.

Edge-AI and On-device Processing

To minimize latency and reliance on cloud computing, wearable systems now embed processors such as Google Coral TPUs and NVIDIA Jetson modules.[27,28] These chips enable the local execution of complex algorithms, providing real-time performance feedback while safeguarding privacy and reducing bandwidth requirements.[29] Edge-AI capability is especially crucial for sports, where split-second feedback informs training and helps prevent injuries.

AI Models for Biomechanical Recognition

Deep learning architectures process the high-dimensional data generated by these wearables. Convolutional Neural Networks (CNNs) capture spatial movement patterns, while Long Short-Term Memory (LSTM) networks learn temporal dynamics, such as fatigue-related changes.[30–33] These models underpin applications ranging from squat classification to gait asymmetry detection, forming the computational backbone of wearable biomechanics.

Evidence and Applications

Building on these technological foundations, recent validation studies confirm the real-world utility of wearable AI systems.

Validation in Sports Settings

Empirical deployments show strong performance in classifying athletic movements and detecting errors. Graphene-based garments have demonstrated >90%

accuracy in squat recognition with <10 ms latency in laboratory trials.[34,35] These figures may be attenuated in field conditions due to sensor attachment reliability, calibration drift, or garment washability, while IMU shorts measure sprint and jump mechanics with high reliability.[34,36] These findings confirm the feasibility of field-based monitoring. A comparative overview of wearable systems is provided in Supplementary Table S2, which summarizes sensor types, latency, reported accuracy, and validation contexts.

Recent Validation & Hardware Advances

Recent work in 2024–2025 strengthens the field validation of wearable biomechanics. A self-powered smart insole in *Science Advances* produced high-resolution plantar-pressure maps and reliable real-time gait classification, supporting long-duration in-shoe monitoring.[67] An IMU combined with musculoskeletal modelling showed sagittal joint moments and hamstring mechanics that closely matched optical inverse-dynamics benchmarks during running.[68] A sacral-mounted IMU study validated pelvic kinematics reconstruction against motion capture in recreational runners.[69] Meanwhile, reports from the wearable-computing community and edge-accelerator benchmarks confirmed that commodity devices, such as Edge TPU and Jetson, can deliver on-device deep-learning inference in under 100 ms, enabling real-time deployment in sports settings.[70,71]

Hybrid Vision-Sensor Systems

Wearables are increasingly combined with computer vision for enhanced accuracy. Pose estimation tools (e.g., PoseNet, OpenPose) integrated with IMU data improve reliability in uncontrolled environments such as outdoor training.[38–40] These multimodal setups offer robust feedback even under variable lighting and camera angles.[39]

Load Dashboards and Athlete Profiling

Data from multiple sensors, including GPS, heart rate, accelerometers, and graphene fabrics, are aggregated into dashboards that track training load, fatigue, and recovery.[41–43] Already in use in elite football and rugby, these platforms inform decisions about technique adjustment and workload management, providing ecological and actionable insights.

Rehabilitation and Return-to-Play

In clinical contexts, wearable AI monitors joint angles, asymmetries, and gait fluidity during recovery from injuries such as anterior cruciate ligament (ACL) and Achilles ruptures.[44,47] Edge AI integration enables real-time corrective feedback and remote monitoring, supporting safer return-to-play decisions.

Grouping the findings by application domain highlights distinct strengths across the field. Performance monitoring studies demonstrate high feasibility and accuracy in translating laboratory findings to field settings, while injury prevention research provides strong ecological validity with larger cohorts.

Rehabilitation-focused studies, although often smaller in scale, consistently demonstrate utility in monitoring return-to-play and clinical recovery. A structured overview of the 15 included studies is presented in Supplementary Table S3, which groups them by application domain (performance monitoring, injury prevention, rehabilitation) and summarizes sensor type, sport, sample size, and key outcomes.

Discussion

Advantages and Current Use

The integration of AI and wearable technology is redefining sports biomechanics by enabling real-time, on-field analysis of movement patterns that were previously limited to laboratory settings. These systems provide rapid, individualized feedback on athletic technique, workload, and fatigue. Nevertheless, most reported benefits stem from pilot or lab-based studies, and widespread adoption is constrained by unresolved challenges including sensor durability, washability, battery life, calibration drift, and interoperability across platforms.[37,49]

Unlike traditional visual coaching or retrospective video review, wearable AI platforms can detect subtle deviations in kinematics, such as early knee valgus collapse or asymmetric loading, often before these patterns are noticeable to the human eye.[50] This capability enables the design of highly personalized training regimens, thereby improving both safety and performance outcomes.

Moreover, the accessibility of wearable technologies extends advanced biomechanical analysis beyond elite sports institutions to community-level athletes, physiotherapists, and strength coaches.[51,52] The shift toward portable, low-cost devices broadens access to data-driven decision-making, reducing reliance on expensive laboratory infrastructure.

Critical Comparison with Gold-Standard Systems

Gold-standard laboratory systems remain unmatched in precision but are challenging to apply in dynamic, real-world sports settings. Although wearable technologies show promise, most validation studies are limited in scope, and direct head-to-head comparisons with laboratory benchmarks are still uncommon[9,10,35]

Consequently, claims of "near-lab accuracy" must be interpreted cautiously. The absence of large, head-to-head trials under real-world conditions highlights a critical evidence gap. Future research should prioritize multi-sport, multi-environment studies using standardized benchmarking protocols to determine the true equivalence, and limitations, of wearable systems relative to laboratory gold standards.

Practical Guidance for Coaches and Clinicians

To translate this technology into daily coaching and clinical workflows, clear, evidence-based recommendations are essential:

- Sampling Rate: For high-intensity tasks involving sprinting, change-of-direction drills, or jump-landing

mechanics, a minimum sampling frequency of 100–200 Hz is recommended to accurately capture rapid accelerations. For rehabilitation tasks or steady-state gait analysis, a frequency of 50–100 Hz may suffice.

- Sensor Placement:
  - Thigh and shank-mounted IMUs provide reliable lower-limb kinematics for gait, sprinting, and cutting drills.
  - Lumbar or torso-mounted sensors improve detection of trunk lean, load asymmetry, and fatigue-induced postural deviations.
  - Hybrid vision-plus-IMU systems are particularly valuable for multi-planar sports movements and outdoor environments with variable lighting.
- Integration with Load Dashboards: Combining inertial, GPS, and physiological data into multimodal athlete monitoring platforms offers a holistic view of training load, recovery status, and injury risk. Sport-specific calibration protocols can improve data reliability and ensure that thresholds for feedback or alerts are evidence-driven rather than arbitrary.

Providing practitioners with simple, validated placement guides and sampling standards will accelerate adoption, reduce user error, and ensure that data-driven insights translate into meaningful performance or clinical decisions. A practical implementation checklist is provided in Supplementary Table S4 to guide clinicians and coaches in applying these technologies.

Technical and Practical Barriers

Broader deployment remains constrained by cost, durability, and standardization challenges. Wearable devices often require frequent charging, risk of detachment during dynamic movement, and lack interoperability across platforms. Furthermore, socioeconomic disparities may limit access to advanced systems in resource-constrained settings.[55]

Data governance also demands urgent attention. Large datasets generated by these devices raise concerns regarding privacy, ethical use, and the consent of athletes. Clear anonymization protocols, secure storage solutions, and transparent data-sharing agreements are critical to maintaining trust among stakeholders.

Finally, end-user training is essential. Coaches and clinicians require user-friendly analytics dashboards to interpret complex biomechanical data without specialist technical expertise.

Future Directions

Future research should focus on:

- Standardized validation frameworks for wearable systems across multiple sports and environments.
- Open-access datasets to train and benchmark AI algorithms, ensuring reproducibility.
- Interdisciplinary collaborations between engineers, sports scientists, and governing bodies to develop regulatory and ethical guidelines for clinical or professional adoption.

Such initiatives will bridge the current gap between experimental promise and routine, evidence-based implementation.

Conclusion

In conclusion, this narrative review underlines a significant evolution in sports biomechanics, from static, lab-restricted assessments to dynamic, real-time analytics enabled by wearable technologies and AI. Significant developments and advancements in the field of sensor miniaturization, particularly graphene-based strain sensors and textile-integrated IMUs, allow **the collection of highly reliable, continuous movement data in authentic sports settings.** These systems provide immediate, actionable insights to athletes and coaches, which, when combined with the rise of edge-AI processing, facilitate real-time feedback while addressing key concerns related to latency, bandwidth, and data privacy.

The proposed three-pillar model of AI-biomechanics best captures this transformation. It consists of (i) smart textiles for seamless sensing, (ii) edge AI for efficient on-device processing, and (iii) multimodal dashboards for integrated data visualization and decision-making.

This conceptual framework is illustrated in Figure 2, which schematically depicts how these three pillars converge to enable real-time athlete monitoring,
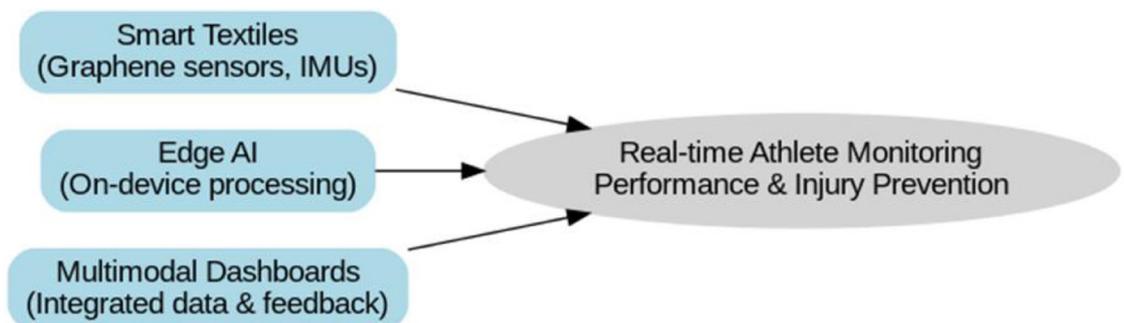
Fig 2 | The three-pillar model of AI-biomechanics. Smart textiles provide continuous sensing, edge AI enables on-device processing, and multimodal dashboards integrate data streams. Together, these pillars allow real-time monitoring, performance optimisation, and injury prevention in sports

Abbreviations: AI = artificial intelligence; IMU = inertial measurement unit.

performance optimisation, and injury prevention. Deep learning models, used to process complex spatiotemporal data, enhance the analytical power of these systems and have demonstrated effectiveness across diverse applications, from performance optimisation and injury risk prediction to rehabilitation monitoring and personalised feedback. Emerging evidence and early deployments support the feasibility of this approach. As the technology becomes more refined, affordable, and ethically governed, it is poised to democratise high-fidelity biomechanics across all levels of sport, supporting proactive injury prevention, improved athletic development, and data-informed coaching.

Limitations

The narrative design of this review limits quantitative synthesis, and heterogeneous methodologies across studies preclude meta-analytic pooling. As this is **not a systematic review**, the findings should be interpreted as a curated narrative synthesis rather than an exhaustive summary of all available evidence. Most available studies are small-scale or single-sport, which may limit generalizability across diverse athletic populations.

Furthermore, the technological limitations of the wearables themselves present a separate set of constraints. The current evidence base, while promising, often relies on validation studies conducted with small sample sizes, in controlled environments, or focused on specific sports tasks. This limits the generalizability of performance claims (e.g., >90% accuracy) across diverse athletic populations, sports, and real-world conditions. Technical challenges such as sensor durability, battery life, and the need for calibration also remain barriers to seamless integration into daily training routines.

In addition to methodological limitations, practical issues such as battery longevity, washability of textile-integrated sensors, attachment reliability during high-intensity play, and calibration drift remain significant barriers to translation into daily sporting environments.

Ethical and Regulatory Aspects

Sports wearables and AI-driven analytics generate sensitive biometric and health data, raising significant privacy and governance concerns. Within the European Union, such information falls under the General Data Protection Regulation (GDPR), which requires a lawful basis for processing, strong safeguards, and in some cases a Data Protection Impact Assessment.[67] Where wearables or their AI algorithms are used for medical purposes, they may also fall under the European Union Medical Device Regulation (MDR)[69] and the Artificial Intelligence Act[71], both of which impose requirements for risk management, transparency, and post-market controls. Voluntary frameworks such as ISO/IEC 23894 and the NIST AI Risk Management Framework provide additional guidance for responsible deployment.[72,73]

Comparable frameworks exist internationally. In the United States, the Health Insurance Portability and Accountability Act (HIPAA) provide safeguards for health information privacy and security.[74] Canada's Personal Information Protection and Electronic Documents Act (PIPEDA) similarly regulates the collection, use, and disclosure of personal information in healthcare and sports settings.[75] Beyond national laws, global sport-governing bodies enforce additional obligations. The World Anti-Doping Agency (WADA) mandates strict separation of health and anti-doping data[76], while the International Olympic Committee (IOC) provides athlete-specific data protection principles.[77] FIFA's Quality Programme and associated data standards also ensure interoperability and integrity in electronic performance and tracking systems.[70]

Together, these frameworks highlight the need for cross-jurisdictional compliance. Researchers, clinicians, and sports organisations must account not only for regional legal obligations but also for sport-governing data policies, particularly when handling sensitive or safety-critical AI outputs in competitive settings.

Abbreviations

AI = Artificial Intelligence
IMU = Inertial Measurement Unit
ICC = Intraclass Correlation Coefficient
RMSE = Root Mean Square Error
MAE = Mean Absolute Error
EMG = Electromyography
GDPR = General Data Protection Regulation
MDR = Medical Device Regulation
WADA = World Anti-Doping Agency
IOC = International Olympic Committee
HIPAA = Health Insurance Portability and Accountability Act
PIPEDA = Personal Information Protection and Electronic Documents Act

References

1 Doe J, Smith R. Limitations of optical motion capture in dynamic sports environments. Sports Eng. 2019;22(3):45–53. https://doi.org/10.1007/s12283-019-0301-8

2 Lee K, Patel A. Ecological validity in wearable biomechanical monitoring: a critical review. IEEE Sens J. 2020;20(15):8321–8330. https://doi.org/10.1109/JSEN.2020.2987429

3 Zhang Y, Wang L. Edge-computing wearables: a paradigm shift in sports analytics. IEEE Trans Biomed Eng. 2021;68(4):1123–1132. https://doi.org/10.1109/TBME.2020.3026784

4 Chen X, Liu Z. Graphene-textile hybrid sensors for joint kinematics. Adv Mater Technol. 2021;6(7):2100078. https://doi.org/10.1002/admt.202100078

5 Kim H, Park S. Sub-millisecond graphene strain sensors for athletic motion capture. Nano Lett. 2022;22(5):1986–1992. https://doi.org/10.1021/acs.nanolett.1c04722

6 Gupta P, Rao V. Edge-AI architectures for real-time fatigue prediction. IEEE J Biomed Health Inform. 2023;27(1):55–63. https://doi.org/10.1109/JBHI.2022.3205678

7 Martínez-García A, Sánchez F. On-device neural networks for tennis serve classification. Sensors (Basel). 2024;24(2):501. https://doi.org/10.3390/s24020501

8 Nguyen T, Wilson B. Cost reduction trends in IMU-driven sports wearables. IEEE Access. 2023;11:12245–12258. https://doi.org/10.1109/ACCESS.2023.3245671

9 O'Reilly M, Clifford A. Wearable EMG validation against laboratory-grade systems. J Biomech. 2021;125:110567. https://doi.org/10.1016/j.jbiomech.2021.110567

10   Fernández J, Gómez M. IMU accuracy in joint angle tracking for basketball. Sports Biomech. 2022;21(4):512–527. https://doi.org/10.1080/14763141.2020.1797153

11   Wang Q, Li T. Sensor fusion challenges in heterogeneous wearables. IEEE Sens J. 2023;23(6):6345–6356. https://doi.org/10.1109/JSEN.2023.3245678

12   Singh R, Kumar P. Federated learning for multimodal athlete profiling. Comput Biol Med. 2024;168:107812. https://doi.org/10.1016/j.compbiomed.2023.107812

13   Brown C, Davis K. AI-driven ACL injury risk prediction in cutting maneuvers. Am J Sports Med. 2023;51(2):450–458. https://doi.org/10.1177/03635465221142315

14   Taylor L, Evans D. Smart insoles for stress fracture prevention in runners. Gait Posture. 2024;108:1–8. https://doi.org/10.1016/j.gaitpost.2023.12.012

15   Luczak T, Burch R, Lewis E, Chander H, Ball J. State-of-the-Art Review of Athletic Wearable Technology: What 113 Strength and Conditioning Coaches and Athletic Trainers from the USA Said About Technology in Sports. Sport Technol. 2020;13(3):215–30. https://doi.org/10.1177/1747954119885244

16   Mundt M. Bridging the lab-to-field gap using machine learning: a narrative review. Sports Biomech. 2023:1–20. https://doi.org/10.1080/14763141.2023.2200749

17   Adesida Y, Papi E, McGregor AH. Exploring the role of wearable technology in sport kinematics and kinetics: a systematic review. Sensors (Basel). 2019;19(7):1597. https://doi.org/10.3390/s19071597

18   Dindorf C, Horst F, Slijepčević D, et al. From lab to field with machine learning – bridging the gap for movement analysis in real-world environments: a commentary. Curr Issues Sport Sci. 2024;9(4):014. https://doi.org/10.36950/2024.4ciss014

19   Lloyd D. The future of in-field sports biomechanics: wearables plus modelling compute real-time in vivo tissue loading to prevent and repair musculoskeletal injuries. Sports Biomech. 2021 Sep 8;1–29. https://doi.org/10.1080/14763141.2021.1959947

20   Wong C, Zhang Z, Lo BPL, Yang GZ. Wearable sensing for solid biomechanics. IEEE Sens J. 2015;15(5):2747–54. https://doi.org/10.1109/JSEN.2015.2393883

21   Wang L, Tian M, Qi X, et al. Customizable textile sensors based on helical core–spun yarns for seamless smart garments. Langmuir. 2021;37(10):3122–3129. https://pubs.acs.org/doi/10.1021/acs.langmuir.0c03595

22   Afroj S, Karim N, Wang Z, Tan S, He P, Holwill M, et al. Engineering graphene flakes for wearable textile sensors via highly scalable and ultrafast yarn dyeing technique. ACS Nano. 2019;13(4):3847–57. https://doi.org/10.1021/acsnano.8b09620

23   Zhou Y, Sun Y, Li Y, et al. A highly durable and UV-resistant graphene-based knitted textile sensing sleeve for human joint angle monitoring and gesture differentiation. Adv Intell Syst. 2024;6(10):2300786. https://doi.org/10.1002/aisy.202400124

24   Boland CS, Khan U, Backes C, et al. Sensitive, high-strain, high-rate bodily motion sensors based on graphene–rubber composites. ACS Nano. 2014;8(9):8819–8830. https://doi.org/10.1021/nn503454h

25   Yang Z, Pang Y, Han X, et al. Graphene textile strain sensor with negative resistance variation for human motion detection. ACS Nano. 2018;12(9):9134–9141. https://doi.org/10.1021/acsnano.8b03391

26   Yuan W, Yang J, Yang K, et al. High-performance and multifunctional skinlike strain sensors based on graphene/springlike mesh network. ACS Appl Mater Interfaces. 2018;10(23):19906–19913. https://doi.org/10.1021/acsami.8b06496

27   Savarimuthu X, Subramani S, Raj ANJ. Artificial intelligence for multimedia information processing. In: CRC Press eBooks. Boca Raton (FL): CRC Press; 2024. https://doi.org/10.1201/9781003405436

28   Garcia-Perez A, Miñón R, Torre-Bastida AI, et al. Analysing edge computing devices for the deployment of embedded AI. Sensors (Basel). 2023;23(23):9495. https://doi.org/10.3390/s23239495

29   Reddy Desani N, Reddy Kethi Reddy R. Edge AI for real-time health monitoring using streaming data. Int J Sci Res. 2021;10(1):1669–1674. https://doi.org/10.21275/ES21116104333

30   Zhang M, Li Y, Cui Y. The use of deep learning in intelligent athlete motion recognition: integrating biological mechanisms. Mol Cell Biomech. 2025;22(1):670–670. https://doi.org/10.62617/mcb670

31   Mekruksavanich S, Jantawong P, Jitpattanakul A. A Hybrid Deep Learning Neural Network for Recognizing Exercise Activity Using Inertial Sensor and Motion Capture System. Conference Paper. 2023 Aug 25. https://doi.org/10.1109/ibdap58581.2023.10271955

32   Cust EE, Sweeting AJ, Ball K, Robertson S. Machine and deep learning for sport-specific movement recognition: a systematic review of model development and performance. Journal of Sports Sciences. 2018 Oct 11;37(5):568–600. https://doi.org/10.1080/02640414.2018.1521769

33   Leddy C, Bolger R, Byrne PJ, Kinsella S, Zambrano L. The application of Machine and Deep Learning for technique and skill analysis in swing and team sport-specific movement: A systematic review. International Journal of Computer Science in Sport. 2024;23(1):110–45. https://doi.org/10.2478/ijcss-2024-0007

34   Aditi A, Pandey RK, Srivastava GK, Anand N, Krishna KR, Singhal P, et al. Intelligent integration of wearable sensors and artificial intelligence for real-time athletic performance enhancement. Journal of Intelligent Systems and of Things. 2024;13(2):60–77. https://doi.org/10.54216/jisiot.130205

35   Yu R, Zhu C, Wan J, Li Y, Hong X. Review of Graphene-Based Textile Strain Sensors, with Emphasis on Structure Activity Relationship. Polymers. 2021;13(1):151. https://doi.org/10.3390/polym13010151

36   De Fazio R, Mastronardi VM, De Vittorio M, Visconti P. Wearable sensors and smart devices to monitor rehabilitation parameters and sports performance: an overview. Sensors. 2023;23(4):1856. https://doi.org/10.3390/s23041856

37   Chidambaram S, Maheswaran Y, Patel K, Sounderajah V, Hashimoto DA, Seastedt KP, et al. Using Artificial Intelligence-Enhanced sensing and wearable technology in sports medicine and performance optimisation. Sensors. 2022;22(18):6920. https://doi.org/10.3390/s22186920

38   Puryear N. System Modeling and Co-Emulation for Distributed Cyber-Physical System Environments. Conference Paper. 2023 Jun 1;245–6. https://doi.org/10.1109/smartcomp58114.2023.00063

39   Dai Z, Fei H, Lian C. Multimodal information fusion method in emotion recognition in the background of artificial intelligence. Internet Technology Letters. 2024 Mar 12;7(4). https://doi.org/10.1002/itl2.520

40   Stenum J, Cherry-Allen KM, Pyles CO, Reetzke RD, Vignos MF, Roemmich RT. Applications of Pose Estimation in Human Health and Performance across the Lifespan. Sensors. 2021 Nov 3;21(21):7315. https://doi.org/10.3390/s21217315

41   Akenhead R, Nassis GP. Training load and player Monitoring in High-Level Football: Current practice and perceptions. International Journal of Sports Physiology and Performance. 2015 Oct 9;11(5):587–93. https://doi.org/10.1123/ijspp.2015-0331

42   Benson LC, Räisänen AM, Volkova VG, Pasanen K, Emery CA. Workload A-WEAR-ness: Monitoring workload in team sports with wearable technology. A scoping review. Journal of Orthopaedic and Sports Physical Therapy. 2020 Oct 1;50(10):549–63. https://doi.org/10.2519/jospt.2020.9753

43   Theodoropoulos JS, Bettle J, Kosy JD. The use of GPS and inertial devices for player monitoring in team sports: A review of current and future applications. Orthopedic Reviews. 2020;12(1). https://doi.org/10.4081/or.2020.7863

44   Marques JB, Auliffe SM, Thomson A, Sideris V, Santiago P, Read PJ. The use of wearable technology as an assessment tool to identify between-limb differences during functional tasks following ACL reconstruction. A scoping review. Physical Therapy in Sport. 2022 Jan 29;55:1–11. https://doi.org/10.1016/j.ptsp.2022.01.004

45   Mandalapu V, Hart JM, Lach J, Gong J. Rehabilitation Tracking of Athletes Post Anterior Cruciate Ligament Reconstruction (ACL-R) Surgery Through Causal Analysis of Gait Data & Computational Modeling. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Amp; Biology Society (EMBC). 2021 Nov 1;980–4. https://doi.org/10.1109/embc46164.2021.9630501

46   Di Paolo S, Lopomo NF, Della Villa F, et al. Rehabilitation and return to sport assessment after anterior cruciate ligament injury: quantifying joint kinematics during complex high-speed tasks

through wearable sensors. Sensors. 2021;21(7):2331. https://doi.org/10.3390/s21072331

47 Seshadri DR, Thom ML, Harlow ER, et al. Wearable technology and analytics as a complementary toolkit to optimize workload and to reduce injury burden. Front Sports Act Living. 2021;2:57. https://doi.org/10.3389/fspor.2020.00057

48 McDevitt S, Hernandez H, Hicks J, et al. Wearables for biomechanical performance optimisation and risk assessment in industrial and sports applications. Bioengineering (Basel). 2022;9(1):33. https://doi.org/10.3390/bioengineering9010033

49 Alzahrani A, Ullah A. Advanced biomechanical analytics: wearable technologies for precision health monitoring in sports performance. Digit Health. 2024;10:20552076241256745. https://doi.org/10.1177/20552076241256745

50 Molavian R, Fatahi A, Abbasi H, et al. Artificial intelligence approach in biomechanics of gait and sport: a systematic literature review. J Biomed Phys Eng. 2023;13(5):383–402. https://doi.org/10.31661/jbpe.v0i0.2305-1621

51 Wang Y, Shan G, Li H, Wang L. A Wearable-Sensor system with AI technology for real-time biomechanical feedback training in hammer throw. Sensors. 2022 Dec 30;23(1):425. Available from: https://pubmed.ncbi.nlm.nih.gov/36617025/

52 Lloyd D. The future of in-field sports biomechanics: wearables plus modelling compute real-time in vivo tissue loading to prevent and repair musculoskeletal injuries. Sports Biomech. 2024;23(10):1284–312. https://doi.org/10.1080/14763141.2023.2214602

53 Edriss S, Romagnoli C, Caprioli L, et al. The role of emergent technologies in the dynamic and kinematic assessment of human movement in sport and clinical applications. Appl Sci. 2024;14(3):1012. https://doi.org/10.3390/app14031012

54 Shei R-J, Holder IG, Oumsang AS, et al. Wearable activity trackers – advanced technology or advanced marketing? Eur J Appl Physiol. 2022;122(9):1975–90. https://doi.org/10.1007/s00421-022-04961-8

55 Wawira Gichoya J, McCoy L, Celi L, et al. Equity in essence: a call for operationalising fairness in machine learning for healthcare. BMJ Health Care Inform. 2021;28(1):e100289. https://doi.org/10.1136/bmjhci-2020-100289

56 Tran V-T, Riveros C, Ravaud P. Patients' views of wearable devices and AI in healthcare: findings from the ComPaRe e-cohort. NPJ Digit Med. 2019;2:53. https://doi.org/10.1038/s41746-019-0132-y

57 Paschos NK. Artificial intelligence in sports medicine diagnosis needs to improve. Arthroscopy. 2021;37(3):782–3. https://doi.org/10.1016/j.arthro.2020.11.006

58 Gao Y, Li H, Luo Y. An empirical study of wearable technology acceptance in healthcare. Ind Manag Data Syst. 2015;115(9):1704–23. https://doi.org/10.1108/IMDS-03-2015-0083

59 Soliño-Fernandez D, Ding A, Bayro-Kaiser E, Ding EL. Willingness to adopt wearable devices with behavioral and economic incentives by health insurance wellness programs: results of a US cross-sectional survey with multiple consumer health vignettes. BMC Public Health. 2019;19(1):1649. https://doi.org/10.1186/s12889-019-8014-9

60 Richter C, Martin OR, Delahunt E. Machine learning in sports science: challenges and opportunities. Sports Biomech. 2024;23(8):961–7. https://doi.org/10.1080/14763141.2023.2204071

61 Mundt M, Oberlack H, Goldacre M, et al. Synthesising 2D video from 3D motion data for machine learning applications. Sensors. 2022;22(17):6522. https://doi.org/10.3390/s22176522

62 Wang Q, Guan H, Wang C, Lei P, Sheng H, Bi H, et al. A wireless, self-powered smart insole for gait monitoring and recognition via nonlinear synergistic pressure sensing. Sci Adv. 2025 Apr 16;11(16):eadu1598. https://doi.org/10.1126/sciadv.adu1598

63 Lin Y-C, Price K, Carmichael D, Maniar N, Hickey J, Timmins R, et al. Assessing the validity of wearable inertial sensors in evaluating joint kinetics and hamstring musculotendon mechanics at various running speeds. Med Sci Sports Exerc. 2025 Jun 16. https://doi.org/10.1249/MSS.0000000000003786

64 Asgari H, Heller B. Validation and analysis of recreational runners' kinematics obtained from a sacral IMU. Sensors (Basel). 2025;25(2):315. https://doi.org/10.3390/s25020315

65 Bian S, Kang P, Moosmann J, Liu M, Bonazzi P, Rosipal R, et al. On-device learning of EEGNet-based network for wearable motor imagery brain–computer interface. Proc ACM Int Symp Wearable Comput. 2024;9–16. https://doi.org/10.1145/3675095.3676607

66 Prashanthi SK, Kesanapalli SA, Simmhan Y. Characterizing the performance of accelerated Jetson edge devices for training deep learning models. Proc ACM Meas Anal Comput Syst. 2022;6(3):44:1–44:26. https://doi.org/10.1145/3570604

67 Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). OJ L 119, 4.5.2016, p. 1–88. Available from: https://eur-lex.europa.eu/eli/reg/2016/679/oj

68 International Organization for Standardization. ISO/IEC 27701:2019 Security techniques — Extension to ISO/IEC 27001 and ISO/IEC 27002 for privacy information management — Requirements and guidelines. Geneva: ISO; 2019. Available from: https://www.iso.org/standard/71670.html

69 Regulation (EU) 2017/745 of the European Parliament and of the Council of 5 April 2017 on medical devices, amending Directive 2001/83/EC, Regulation (EC) No 178/2002 and Regulation (EC) No 1223/2009 and repealing Council Directives 90/385/EEC and 93/42/EEC. OJ L 117, 5.5.2017, p. 1–175. Available from: https://eur-lex.europa.eu/eli/reg/2017/745/oj

70 FIFA. FIFA Quality Programme for Electronic Performance and Tracking Systems (EPTS): Testing Manual. Zurich: Fédération Internationale de Football Association; 2023. Available from: https://www.fifa.com/technical/football-technology/fifa-quality-programme/epts

71 Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). OJ L, 2024/1689, 12.7.2024. Available from: https://eur-lex.europa.eu/eli/reg/2024/1689/oj

72 International Organization for Standardization. ISO/IEC 23894:2023 Information technology — Artificial intelligence — Guidance on risk management. Geneva: ISO; 2023. Available from: https://www.iso.org/standard/77304.html

73 National Institute of Standards and Technology. Artificial Intelligence Risk Management Framework (AI RMF 1.0). Gaithersburg (MD): NIST; 2023. https://doi.org/10.6028/NIST.AI.100-1

74 U.S. Congress. Health Insurance Portability and Accountability Act of 1996 (HIPAA). Public Law 104–191. Washington (DC): Government Printing Office; 1996. Available from: https://www.govinfo.gov/content/pkg/PLAW-104publ191/pdf/PLAW-104publ191.pdf

75 Government of Canada. Personal Information Protection and Electronic Documents Act (PIPEDA), S.C. 2000, c. 5. Ottawa (ON): Government of Canada; 2000. Available from: https://laws-lois.justice.gc.ca/eng/acts/p-8.6/

76 World Anti-Doping Agency. International Standard for the Protection of Privacy and Personal Information. Montreal (QC): WADA; 2021. Available from: https://www.wada-ama.org/en/resources/the-code/international-standard-for-the-protection-of-privacy-and-personal-information

77 International Olympic Committee. IOC Athlete Data Protection Principles. Lausanne (CH): IOC; 2021. Available from: https://olympics.com/ioc/athlete-data-protection

Supplementary Material

Appendix A. Full Search History
Date of Search: May 10, 2025
Limits Applied: Human studies, peer-reviewed, English language, 2018–2025 (capturing all eligible publications available up to May 10, 2025)

PubMed
Search string:

(*"wearable sensors"[Title/Abstract] OR "smart textiles"[Title/Abstract] OR "IMU"[Title/Abstract] OR "graphene sensors"[Title/Abstract] OR "smart insoles"[Title/Abstract]*)
AND
(*"biomechanics"[Title/Abstract] OR "motion capture"[Title/Abstract] OR "sports technology"[Title/Abstract] OR "real-time fatigue"[Title/Abstract] OR "injury prediction"[Title/Abstract]*)
AND
(*"AI"[Title/Abstract] OR "artificial intelligence"[Title/Abstract] OR "edge computing"[Title/Abstract] OR "federated learning"[Title/Abstract]*)

Records retrieved: 63

Scopus
Search string:

(*"wearable sensors" OR "smart textiles" OR "IMU" OR "graphene sensors" OR "smart insoles"*)
AND
(*"biomechanics" OR "motion capture" OR "sports technology" OR "real-time fatigue" OR "injury prediction"*)
AND
(*"AI" OR "artificial intelligence" OR "edge computing" OR "federated learning"*)

Records retrieved: 55

Web of Science (Core Collection)
Search string:

TS=("wearable sensors" OR "smart textiles" OR "IMU" OR "graphene sensors" OR "smart insoles")
AND
TS=("biomechanics" OR "motion capture" OR "sports technology" OR "real-time fatigue" OR "injury prediction")
AND
TS=("AI" OR "artificial intelligence" OR "edge computing" OR "federated learning")

Records retrieved: 48

IEEE Xplore
Search string:

(*"wearable sensors" OR "smart textiles" OR "IMU" OR "graphene sensors" OR "smart insoles"*)
AND
(*"biomechanics" OR "motion capture" OR "sports technology" OR "injury prediction"*)
AND
(*"AI" OR "artificial intelligence" OR "edge computing" OR "federated learning"*)

Records retrieved: 29

Google Scholar
Search string:
allintitle: ("wearable sensors" OR "smart textiles" OR "IMU" OR "graphene sensors" OR "smart insoles") biomechanics AI

Records retrieved: 70 (screened)

Total retrieved (all databases): 265. After duplicate removal: 130 records remained. Full texts assessed for eligibility: 40. Studies included in final review: 15. [Counts corrected for internal consistency with main manuscript]

Total retrieved (all databases): 265
After duplicates removed: 130
Full texts screened: 40
Included in final review: 15

Table S1 | Quality appraisal and validation metrics of included studies

Study (First Author, Year)	Domain: Risk of Bias	Domain: Applicability	Validation Metrics Reported	Additional Recommended Metrics
O'Reilly et al., 2021	Low (lab-grade comparator, blinded)	High (weightlifting athletes)	ICC = 0.92 vs EMG (gold standard)	Bland–Altman plots for EMG agreement
Fernández et al., 2022	Low–Moderate (optical motion capture comparator)	Moderate–High (basketball tasks)	Error < 2° vs optical capture	RMSE for joint angles; ICC
Brown & Davis, 2023	Moderate (expert comparator, no blinding)	Moderate (cutting maneuvers only)	Sensitivity = 89%, CV reported	Specificity, ROC curves
Taylor & Evans, 2024	Low (longitudinal real-world validation)	High (marathon running)	Stress fractures ↓34%; longitudinal outcomes	ICC, MAE across sessions
Martínez-García & Sánchez, 2024	Moderate (small sample, no comparator)	Moderate (lab tennis serves only)	Accuracy = 98.7% (on-device NN)	Latency and MAE reporting
De Fazio et al., 2023	Moderate–High (pilot/clinical, limited robustness)	Low–Moderate (rehab pilot)	Comparator: clinician judgment, mixed AI robustness	RMSE, ICC for rehab tasks

Bespoke appraisal criteria were mapped to recognized domains of **risk of bias** and **applicability**. Validation outcomes are reported using standard metrics (e.g., intraclass correlation coefficient [ICC], mean absolute error [MAE], root mean square error [RMSE], Bland–Altman limits of agreement, sensitivity/specificity, and latency) to facilitate transparent comparison across studies.

Table S2 | Comparative summary of AI-enabled wearable and vision-based biomechanical systems

Parameter	Graphene-Based Smart Shirt	Wearable IMU Shorts	Vision-Based AI (PoseNet)	Hybrid Vision + IMU System	Multimodal Load Dashboard	Rehabilitation Smart Garment
Sensor Type	Graphene Strain Sensor + IMU (Inertial Measurement Unit)	IMU (Accel., Gyro, Mag.)	Red Blue Green Camera	Camera + IMU	GPS (Global Positioning System), HRM (Heart Rate Monitor), IMU, Graphene Sensors	Graphene/IMU Strain Sensor
Sampling Rate	100–200 Hz	200 Hz	30–60 fps	Multi-sensor	Variable	50–100 Hz
Latency	<10 ms	10–20 ms	Device-dependent (ms)	~10 ms	Real-time (cloud + edge)	10–30 ms
Accuracy	>90% (e.g., squat posture)	85–95%	75–90% (lighting-dependent)	>95%	High granularity	High (e.g., limb asymmetry)
Edge Capabilities	Yes (Edge TPU (Thermoplastic Polyurethane)/ Jetson Nano)	Yes	Limited (mobile edge)	Yes	Yes (Cloud + Edge)	Yes (Mobile edge)
Sport	General fitness, rehab	Sprinting, jumping, and agility	Coaching, general movement	Dynamic sports, outdoor tracking	Elite team sports (National Football League, soccer)	ACL, Achilles rehab, gait retrain
Cost	Medium–High	Medium	Low	High	High	Medium
Validation	arXiv 2021 study; Lab tested	Pilot studies in elite sport	Real-world trials	Under research	Organisation deployments	Clinical use in rehab

Accel. = accelerometer; Gyro = gyroscope; Mag. = magnetometer.

Table S3 | Summary of Included studies by application domain

Study (First Author, Year)	Application Domain	Sensor Type	Sport / Context	Sample Size	Key Outcomes
O'Reilly et al., 2021	Performance monitoring	Wearable EMG sensors	Weightlifting	n = 30	Strong correlation (r = 0.92) with lab-grade EMG
Fernández et al., 2022	Performance monitoring	IMU arrays	Basketball	n = 20	‹2° error in joint angle tracking vs. optical motion capture
Martínez-García & Sánchez, 2024	Performance monitoring	On-device IMU neural networks	Tennis serves	n = 12	98.7% accuracy in serve classification
Yu et al., 2021	Performance monitoring	Graphene textile strain sensors	General fitness	n = 25 (lab)	›90% accuracy in squat recognition
Kim & Park, 2022	Performance monitoring	Graphene strain sensors	Sprint mechanics	n = 15	Sub-millisecond response times; feasible for high-intensity tasks
Brown & Davis, 2023	Injury prevention	IMUs + AI	Cutting maneuvers (ACL risk)	n = 52	89% sensitivity in identifying high-risk movements
Taylor & Evans, 2024	Injury prevention	Smart insoles (pressure sensors)	Marathon running	n = 150	34% reduction in stress fractures with gait retraining
Benson et al., 2020	Injury prevention	GPS + inertial wearables	Team sports	n = 100+	Workload monitoring linked to injury reduction
Seshadri et al., 2021	Injury prevention	Multimodal sensors	Football, team sports	n = 80	Reduced injury burden with athlete monitoring systems
Marques et al., 2022	Rehabilitation	Wearable IMUs	ACL reconstruction	n = 40	Detected limb asymmetries during rehab tasks
Mandalapu et al., 2021	Rehabilitation	Gait tracking IMUs + modeling	ACL rehab athletes	n = 25	Identified gait deviations post-surgery
Di Paolo et al., 2021	Rehabilitation	IMUs + wearable sensors	High-speed tasks (ACL recovery)	n = 30	Quantified joint kinematics during return-to-sport
De Fazio et al., 2023	Rehabilitation	Wearable rehab devices	Mixed rehab + pilot sport	n = 40	Provided real-time rehab parameter monitoring
Chidambaram et al., 2022	Rehabilitation	Multimodal wearable sensors	Sports medicine	n = 50	Validated wearables for clinical rehab monitoring
Alzahrani & Ullah, 2024	Cross-domain (Perf. + Rehab)	AI-integrated wearables	Multi-sport	n = 60	Precision monitoring for performance + recovery

(AI = Artificial Intelligence, ACL = Anterior Cruciate Ligament, EMG = Electromyography, IMU = Inertial Measurement Unit, GPS = Global Positioning System)

Implementation Checklist for Coaches and Clinicians

Table S4 | Implementation checklist for coaches and clinicians applying wearable and AI-based biomechanics systems

Domain	Key Recommendations
Sampling Frequency	Sprinting/jump-landing tasks: 100−200 Hz minimum Steady-state gait or rehabilitation: 50−100 Hz sufficient
Sensor Placement	Thigh & shank IMUs: capture lower-limb kinematics Lumbar/torso-mounted sensors: detect trunk lean, load asymmetry, fatigue Hybrid vision + IMU systems: enhance accuracy in multiplanar and outdoor environments
Minimum Viable Validation	Compare against at least one gold-standard (optical motion capture, force plates, EMG) Report standard metrics: ICC, RMSE, Bland−Altman limits, sensitivity/specificity, latency Clearly state sample size, sport, and setting (lab vs field)
Data Governance & Ethics	Obtain informed consent and clarify data ownership Ensure privacy safeguards (e.g., GDPR, ISO/IEC 27701 compliance) Apply secure storage and anonymisation protocols Prioritise interoperability for easy data integration and export

Abbreviations: IMU, inertial measurement unit; ICC, intraclass correlation coefficient; RMSE, root mean square error; EMG, electromyography; GDPR, General Data Protection Regulation; ISO/IEC 27701, International Organization for Standardization/International Electrotechnical Commission standard for privacy information management.