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Artificial Intelligence in Sports: Opportunities, Challenges, and Future Directions

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ABSTRACT

Artificial intelligence (AI) is increasingly used in sports for movement analysis, performance monitoring, injury research, talent identification, officiating support, and fan services [23]. This review assesses how well the current evidence supports these claims and what uncertainties remain. The strongest evidence is with respect to specific measurement tasks. For instance, a validation study of markerless pose estimation in 5 participants reported mean absolute joint angle errors of 9.7 ± 4.7 degrees for athletic movements and 9.0 ± 3.3 degrees for sports movements [1]. A separate study found that VAR improved decision accuracy from 92.1% to 98.3% across 2,195 matches [2] (again, this refers to video-assisted refereeing, not AI). Prediction-based applications are less settled. Talent-identification studies report ROC-AUC values from about 0.58 to 0.96, but calibration is rarely reported, external validation is uncommon, and 59% of studies were judged at high risk of bias [3]. A return-to-sport review also found that most included studies were rated unclear or high risk in the analysis domain, primarily because external validation remained absent [4]. The data suggest that AI can serve as a measure or decision-support tool, provided it's validated for the specific application. There are no apparent broad predictive or clinical benefits. The next step is to validate this independently, report it properly, involve the practitioner, and set clear rules for using athlete data. This is a narrative review rather than a systematic review, and the sources we've used are not exhaustive. They should not be interpreted as a full representation of the literature that's available.

Keywords: artificial intelligence; sports technology; performance analysis; athlete health; sports analytics; injury prediction; talent identification; data governance

INTRODUCTION

Artificial intelligence encompasses computational methods that perform tasks such as pattern recognition, prediction, and language processing. In sport, machine learning and computer vision analyse movement, classify events, and identify patterns in performance data [6], [7]. These applications sit alongside a wider set of technologies—including GPS units, accelerometers, video review, and motion-capture systems—that may support sport without themselves relying on AI. Keeping that distinction clear is essential when assessing what AI has actually demonstrated.

Several team sports use these technologies. In one survey of practitioners, all 72 respondents supported using GPS in their sport, and 70.8% felt it was important to their success [8]. A separate practitioner interview study highlighted concerns about trust and whether wearable measures provide the information coaches require [9]. Adoption therefore demonstrates both need and operational feasibility, but does not necessarily mean the technology improves performance or reduces injury.

This review examines which applications have the clearest evidence of practical value; where evidence is limited by sample size, representativeness, or study design; how well measurements and predictions generalise; and what privacy, fairness, cost, and access issues need to be addressed. It covers performance

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analysis, training, injury prevention and rehabilitation, talent identification, officiating and fan services. It doesn't cover anti-doping analytics or esports performance.

Review Approach and Evidence Base

This is a narrative synthesis of the reviews, validation studies, practitioner surveys and legal analyses listed below. It is not the output of a systematic database search; we did not preregister a protocol, and we did not use formal screening or inclusion procedures. We selected these sources to exemplify key sport applications and issues in measurement validity, prediction, implementation, and governance.[38]. This is therefore not a comprehensive or replicable review, and the number of studies referenced in any given review should not be taken to indicate the number of studies that we have independently assessed.

The evidence base is uneven. Soccer and basketball receive more attention than many other sports; prediction tasks dominate much of the literature; and reference datasets and consistent assessment measures remain limited [11], [12]. An earlier systematic review of AI for injury-risk assessment and performance prediction in team sports provides some background for this research area [13]. Measurement studies validate their results by comparison with a recognised reference method. Prediction studies use internal validation and various metrics but provide no evidence of calibration or any practical value. Practitioner surveys tell us how the tools are used and perceived but again provide no evidence of any causal effect. Legal analyses will invariably point to governance gaps but won't address those gaps with any data [5]. This review will highlight each type of evidence as we go.

Applications

Performance Analysis

ML models have been used for match outcome prediction, performance assessment, playing style identification and player analysis. Tracking data can improve results beyond notational data alone, though combining data types doesn't always improve accuracy [11]. Computer vision can support event detection, video analysis, and automated highlight creation [16], [17]. These applications should be assessed against sport-specific benchmarks and relevant endpoints. However, metrics are not always consistent, and reference datasets are very limited, particularly for sports other than football [11], [12].

Training and Coaching

GPS and accelerometers are fundamentally measurement technologies rather than AI systems [8]. In one practitioner survey, 87.5% of respondents reported using wearable data to inform their training prescription, and 50% reported using it to inform their competition decisions [8]. This shows that data is collected far more often than it is used to make decisions. There is clearly interest in automating both the technical and the tactical aspects of the process [19]. Reviews of the subject have identified data quality, explainability, and practitioner control as key issues that must be addressed for the technology to be implemented [18]. People using the data should not assume that AI-guided training improves outcomes.

Injury Prevention and Rehabilitation

Researchers have studied injury prediction extensively; however, reported performance metrics vary considerably. A systematic review reported results ranging from 52% accuracy and an AUC of 0.52 to an AUC of 0.87 and an F1-score of 85%. The review also assessed methodological quality as generally sufficient but with room for improvement [20]. Different injury definitions, prediction windows, samples, and validation methodologies mean direct comparison is not possible. The reviews identify external validity, reproducibility and adoption into care pathways as key priorities [21]. Return to sport models are of little value unless they have been externally validated in an independent cohort; to date, no study has done this [4]. They should remain in the research or decision support space until prospective validation demonstrates value in a specific clinical or sporting context.

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Talent Identification and Scouting

Researchers have proposed using machine learning to combine physical, technical, perceptual-cognitive, psychological, and environmental information for youth talent identification. A systematic review of 27 studies found that soccer was the most common sport, samples ranged from 21 to 13,876 athletes, and participants were predominantly male. Reported discrimination varied considerably (ROC-AUC ~0.58 to 0.96) [3]. Calibration was rarely reported, external validation was infrequent, and 59% of studies were considered at high risk of bias [3]. These constraints mean a model's ability to rank or classify cannot be taken as proof that it fairly and accurately identifies long-term potential across clubs, sports, age groups, and demographic groups. Current evidence suggests these systems can be used as supplementary screening and decision-support tools, with human review and monitoring of error rates for disparities. It does not support using such systems to replace scouts or coaches.

Officiating and Decision Support

The most significant quantified operational outcome in the review is with VAR. In 2,195 competitive matches across 13 countries, decision accuracy on potentially match-changing incidents increased from 92.1% to 98.3% after VAR was introduced [2]. The median check time was 22 seconds, median on-field review time 62 seconds, and median VAR-only review time 15 seconds [2]. VAR is a human-based video review process and should not be described as AI evidence unless the AI element under assessment is specifically identified.

Researchers are also exploring computer vision systems for automated offside detection. The referenced YOLOv8 paper evaluates a prototype on 400 annotated instances and claims 83.0% overall accuracy on 240 test instances [22]. That doesn't mean the prototype's performance or specifications are acceptable for a deployed professional semi-auto offside system. Any claims about the deployed system, the camera setup, or the accuracy threshold need support from a separate, clearly identified source. More generally, the referee's role, rule interpretation, liability, and review time all affect the system's practical performance [26].

Fan Engagement and Sports Management

Fan-facing applications include chatbots, virtual assistants, ticketing support, and AI-assisted video content [16],[17]. These could improve access to information or content delivery, but the cited literature is predominantly descriptive and from an industry perspective. Independent evaluation would be required to assess actual user outcomes in terms of accessibility, reliability and personal data. It would be wrong to make broad claims about the fan experience being improved.

Potential Benefits and Current Evidence

The key technical advantage is that it makes movement measurement far more accessible. A markerless pose estimation validation study reported joint angle errors for both athletic and sporting movements [1]. A separate multi-camera study found that most mean absolute errors were under 30mm and noted that erroneous tracking would need correction [24]. So markerless methods could be a useful alternative when marker-based capture isn't feasible. However, they don't show that accuracy is the same across movements, camera configurations, athletes, or decisions. Accuracy has to be judged in the context of the specific application.

Decision support can help practitioners or officials review complex events, though its benefit depends heavily on the system and context. VAR's measured improvement in accuracy is relevant as evidence of the value of video review [2]; it is not evidence that AI in general improves officiating.

Wearable data can support load management, and AI models can help structure risk information [8], [14]. Still, practitioner adoption and model results are not sufficient to show that the models actually prevent injury. Smart textiles and VR are both areas with potential, but issues around comfort, durability, cost and the transfer from the simulated to the real world all require further work [25], [31].

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Challenges and Limitations

Data Privacy and Governance

Athlete data is fundamentally biometric, health, movement and performance data. The issue of who owns and controls that data is very much a matter of variation, particularly in terms of the movement of data between teams, technology providers, leagues and the various analytics providers [5]. Secure handling guidance in itself will not deal with the issues of ownership, access, reuse, retention or benefit sharing. In elite sport, formal consent may not give athletes a genuinely voluntary choice where there is an imbalance of power between the athlete and the organisation [5]. A survey of professional footballers found concern about the potential misuse of biometric data. However, one must interpret those findings cautiously given the sample and study design [27]. Governance needs to address access, correction, deletion, retention, secondary use, security and independent oversight.

Bias and Fairness

The results models produce depend on the data's demographics and how success is defined. Most talent-identification research focuses on male participants and covers only a small selection of sports [3]. Broader reviews also show that interpretability has not been studied much [15]. Labels from past selection processes may reflect current practices. As a result, models trained on these labels might continue those same practices. This risk should be tested with data, not assumed based on findings from the cited studies. Evaluations should show how models perform across demographic groups and identify who benefits and who is left out.

Reliability, Validation, and Transparency

The measured results will depend on camera position, occlusion, movement type, and the reference method. Marker-based motion capture is itself subject to experimental error and is therefore not a perfect ground truth [28]. In one study of sports collisions, pose estimation errors varied widely by joint and by observation, with some errors exceeding 50mm [29]. Prediction models also face several issues. Internal validation can be misleading with small samples and/or data leakage, and external validation is rare [3], [4], [15]. Reports should include calibration, uncertainty, class balance, subgroup results and the impact of false positives and false negatives rather than just the headline accuracy or AUC.

Cost, Access, and Implementation

Integrated technology can be expensive and difficult to scale - particularly if it requires equipment, infrastructure, maintenance and specialist staff [37]. GPS tracking can lose accuracy in urban environments - that GPS-specific limitation should not be generalised to all sensors or all indoor environments [37].

Indoor tracking systems require validation under the conditions of the sport and venue in which they will be used. Field studies have often involved small samples and elite adult male athletes [30],[33]. Research concentrated in a few sports may leave other sports and competition levels with systems that have not been validated for their needs [34]. Any assessment of practical value should include access, maintenance, staff training, interoperability, and infrastructure.

Human Judgment and Athlete Experience

Continuous monitoring can support training while increasing surveillance and reducing the athlete's control over their personal data [5]. Practitioners have expressed distrust in some wearable outputs and reported a disconnect between the measures available and the information they actually require [9].

Human monitoring is therefore not an option; athletes and practitioners need to interrogate, contextualise, and meaningfully override the outputs, and responsibility for any resulting decisions must be clearly assigned.

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Priorities for Future Research and Governance

First, they need to be tested in independent multicentre groups that are representative of the sport, the people and the situations in which they will be used [4], [21]. Second, the reports should contain information on calibration, uncertainty, performance in subgroups, data leakage controls, decision-focused measures and discrimination [3], [15]. Third, they should be compared with current practice. Measure the model's impact on outcomes, workload, cost, and decision quality. Fourth, the system should be co-designed with athletes, coaches, clinicians and officials, and there should be clear criteria as to when human review of the output is required [35].

Research should also examine technologies in underrepresented sports and populations, publish reproducible methods and benchmarks where possible (while respecting privacy), and independently verify any commercial claims. For wearables and smart textiles, research should report on durability, comfort, washability, energy consumption, and life cycle cost [31]. VR research should assess transfer to real-world performance rather than just improvement within the VR environment itself [32]. A governance framework is needed to define the rights and boundaries of data collection, access, retention, secondary use, and sharing, with independent oversight and genuine athlete involvement [5].

DISCUSSION

Of the applications looked at, measurement has by far the strongest validation evidence; the prediction-based claims are less well supported. The pose estimation studies report error figures, though accuracy depends heavily on movement and setup [1], [24], [29]. The VAR provides objective evidence of video-assisted decision review [2]. VAR is a separate technology and doesn't validate AI systems. The YOLOv8 offside study remains at the prototype stage and should be described as such [22].

Prediction results need to be treated with caution. Talent identification metrics vary widely; external validation and calibration are rare, and evidence is uneven across demographics [3]. The injury and return to sport literature is similarly plagued by methodological heterogeneity and a lack of external validation [4], [10], [15]. The lack of external validation and variability in metrics mean the accuracy figures cannot be taken as evidence of either clinical utility or fair selection. The real issue is not simply whether the model predicts an outcome, but whether using the model in a decision improves that decision without creating unacceptable harm.

This review has several important limitations. Because this narrative synthesis lacks a documented systematic search, it may omit relevant studies and cannot claim comprehensive coverage. Most of the existing literature focuses on only a few sports [3], and the evidence comes from validation studies, practitioner surveys, narrative reviews, and legal analysis. Consequently, the conclusions should be seen as an evidence-informed assessment of the sources considered rather than a formal ranking of all available systems.

CONCLUSION

AI is used in sport in many areas, but the evidence suggests it is not fundamentally transforming sport. Markerless movement analysis and related measurement tools have proven useful in specific applications [36]. VAR has been shown to improve the accuracy of officiating decisions in the matches studied [2] (again, this result is specific to VAR rather than AI in general). Injury prediction and talent identification models are still hampered by inconsistent methodology, limited external validation, poor calibration, and uneven samples [4]. A model may perform well internally, but that does not guarantee real-world benefit.

Future work should be prospective, independently validated, and reported clearly and relevantly, with direct comparisons to current practice and testing across a range of sports and groups. A clear governance framework should define the athlete's rights and set hard limits on using the data for any other purpose. Until

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those measures are in place, AI should be used only for measurement and decision-making. Any predictive or evaluative use will require far stronger evidence and continued human oversight [3], [4].

REFERENCES

1. T. Fukushima, P. Blauberger, T. G. Russomanno, and M. Lames, "The potential of human pose estimation for motion capture in sports: a validation study," Sports Engineering, vol. 27, no. 1, May 2024, doi: 10.1007/s12283-024-00460-w.
2. J. Spitz, J. Wagemans, D. Memmert, A. M. Williams, and W. Helsen, "Video assistant referees (VAR): The impact of technology on decision making in association football referees," Journal of Sports Sciences, vol. 39, no. 2, pp. 147–153, Aug. 2020, doi: 10.1080/02640414.2020.1809163.
3. Q. Tang, X. Wei, and B. Tan, "The Role of Machine Learning in Talent Identification for Team Sports: A Systematic Review," Journal of Sports Science and Medicine, vol. 25, no. 1, pp. 58–83, 2026, doi: 10.52082/jssm.2026.58.
4. R. Satija and D. Dkhar, "Predictive accuracy of machine learning and markerless gait analysis for return-to-sport following lower extremity injury: a systematic review and meta-analysis," Frontiers in Sports and Active Living, vol. 8, Jun. 2026, doi: 10.3389/fspor.2026.1862870.
5. J. W. Kwon, "Athlete data sovereignty: addressing the legal and policy gaps in sports technology," Frontiers in Sports and Active Living, vol. 7, p. 1742484, Dec. 2025, doi: 10.3389/fspor.2025.1742484.
6. W. X. Zhao, H. Zheng, and Q. Zhang, "Modern Advances in Artificial Intelligence Across the Athletic Domain," Concurrency and Computation Practice and Experience, vol. 37, Apr. 2025, doi: 10.1002/cpe.70068.
7. D. Zhou, J. Keogh, Y. Ma, R. K. Tong, A. R. Khan, and N. R. Jennings, "Artificial intelligence in sport: A narrative review of applications, challenges and future trends," Journal of Sports Sciences, pp. 1–16, Jun. 2025, doi: 10.1080/02640414.2025.2518694.
8. L. Dawson, S. A. McErlain-Naylor, G. Devereux, and M. Beato, "Practitioner Usage, Applications, and Understanding of Wearable GPS and Accelerometer Technology in Team Sports," Journal of Strength and Conditioning Research, vol. 38, no. 7, pp. e373–e382, 2024, doi: 10.1519/JSC.0000000000004781.
9. T. Luczak, R. F. Burch, E. C. Lewis, H. Chander, and J. E. Ball, "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," International Journal of Sports Science & Coaching, vol. 15, no. 1, pp. 26–40, Nov. 2019, doi: 10.1177/1747954119885244.
10. C. Leckey, N. van Dyk, C. Doherty, A. Lawlor, and E. Delahunt, "Machine learning approaches to injury risk prediction in sport: a scoping review with evidence synthesis," British Journal of Sports Medicine, vol. 59, no. 7, pp. 491–500, Nov. 2024, doi: 10.1136/bjsports-2024-108576.
11. M. Klemp, M. Bassek, M. G. Caparrós, L. Bakhtiar, and D. Memmert, "The use of machine learning in performance analysis in invasion games: Umbrella review of reviews," Journal of Sports Sciences, pp. 1–28, Mar. 2026, doi: 10.1080/02640414.2026.2636863.
12. R. Bunker and T. Sušnjak, "The Application of Machine Learning Techniques for Predicting Match Results in Team Sport: A Review," Journal of Artificial Intelligence Research, vol. 73, pp. 1285–1322, 2022, doi: 10.1613/jair.1.13509.
13. J. G. Claudino, D. de O. Capanema, T. V. de Souza, J. C. Serrão, A. C. M. Pereira, and G. P. Nassis, "Current Approaches to the Use of Artificial Intelligence for Injury Risk Assessment and Performance Prediction in Team Sports: a Systematic Review," Sports Medicine - Open, vol. 5, no. 1, p. 28, Jul. 2019, doi: 10.1186/s40798-019-0202-3.
14. C. L. Mușat et al., "Diagnostic Applications of AI in Sports: A Comprehensive Review of Injury Risk Prediction Methods," Diagnostics, vol. 14, no. 22, p. 2516, Nov. 2024, doi: 10.3390/diagnostics14222516.
15. J. Yuan, Q. Zeng, J. Li, Z. Cong, and Y. Zhang, "Machine learning applications in sports injury prediction: A narrative review," Science Progress, vol. 108, no. 4, Oct. 2025, doi: 10.1177/00368504251385956.

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

16. B. T. Naik, M. F. Hashmi, and N. D. Bokde, "A Comprehensive Review of Computer Vision in Sports: Open Issues, Future Trends and Research Directions," Applied Sciences, vol. 12, no. 9, p. 4429, Apr. 2022, doi: 10.3390/app12094429.
17. W. Li et al., "A review of artificial intelligence for sports: Technologies and applications," Intelligent Sports and Health, vol. 1, no. 3, pp. 113–126, Jun. 2025, doi: 10.1016/j.ish.2025.05.001.
18. F. Hammes, A. Hagg, A. Asteroth, and D. Link, "Artificial Intelligence in Elite Sports—A Narrative Review of Success Stories and Challenges," Frontiers in Sports and Active Living, vol. 4, p. 861466, Jul. 2022, doi: 10.3389/fspor.2022.861466.
19. T.-K. Davidson, S. Barrett, J. Toner, and C. Towlson, "Professional soccer practitioners' perceptions of using performance analysis technology to monitor technical and tactical player characteristics within an academy environment: A category 1 club case study," PLoS ONE, vol. 19, no. 3, Mar. 2024, doi: 10.1371/journal.pone.0298346.
20. H. V. Eetvelde, L. D. M. Mendonça, C. Ley, R. Seil, and T. Tischer, "Machine learning methods in sport injury prediction and prevention: a systematic review," Journal of Experimental Orthopaedics, vol. 8, no. 1, p. 27, Jan. 2021, doi: 10.1186/s40634-021-00346-x.
21. J. S. M. Mora, R. A. B. Medina, V. E. Q. Molina, and E. H. H. Rincon, "Beyond the conventional: Artificial intelligence in identifying risk factors in sports injuries. A scoping review," International Journal of Medical Informatics, vol. 214, p. 106408, Mar. 2026, doi: 10.1016/j.ijmedinf.2026.106408.
22. A.-R. Abdel-Fattah et al., "YOLOv8 computer vision for automated offside detection in professional football validated through supervised learning," Scientific Reports, May 2026, doi: 10.1038/s41598-026-52668-4.
23. Rahmani, M., Majedi, N., Hemmatinejad, M., & Jamshidi, A. (2024). Application of Artificial Intelligence in the Sports Industry: A Review Article. 2(2), 20–27. https://doi.org/10.61838/kman.aitech.2.2.4
24. N. Nakano et al., "Evaluation of 3D Markerless Motion Capture Accuracy Using OpenPose With Multiple Video Cameras," Frontiers in Sports and Active Living, vol. 2, p. 50, May 2020, doi: 10.3389/fspor.2020.00050.
25. Z. Xu et al., "Smart Textiles for Personalized Sports and Healthcare," Nano-Micro Letters, vol. 17, no. 1, p. 232, Apr. 2025, doi: 10.1007/s40820-025-01749-6.
26. Asiabar, M. G., Asiabar, M. G., & Asiabar, A. G. (2025). Examining Legal Challenges of Modern Technologies in Sports Arbitration: A Case Study of VAR in Football. https://doi.org/10.14293/pr2199.001551.v1
27. M. G. Asiabar, M. G. Asiabar, and A. G. Asiabar, "Legal Challenges of Wearable Technology Use in Sports Competitions: A Case Study of European Football Leagues," Nov. 15, 2024. doi: 10.20944/preprints202411.0558.v2.
28. S. Colyer, M. Evans, D. Cosker, and A. Salo, "A Review of the Evolution of Vision-Based Motion Analysis and the Integration of Advanced Computer Vision Methods Towards Developing a Markerless System," Sports Medicine - Open, vol. 4, no. 1, p. 24, Jun. 2018, doi: 10.1186/s40798-018-0139-y.
29. R. Blythman, M. Saxena, G. Tierney, C. Richter, A. Smolić, and C. Simms, "Assessment of deep learning pose estimates for sports collision tracking," Journal of Sports Sciences, vol. 40, no. 17, pp. 1885–1900, Sep. 2022, doi: 10.1080/02640414.2022.2117474.
30. Mencarini, E., Rapp, A., Tirabeni, L., & Zancanaro, M. (2019). Designing Wearable Systems for Sports: A Review of Trends and Opportunities in Human–Computer Interaction. IEEE Transactions on Human-Machine Systems, 49(4), 314–325. https://doi.org/10.1109/thms.2019.2919702
31. M. T. Islam et al., "Advancements in functional smart and wearable textiles for sportswear applications," RSC Advances, vol. 15, no. 58, pp. 50206–50232, Jan. 2025, doi: 10.1039/d5ra07231j.
32. S. C. Michalski, A. Szpak, and T. Loetscher, "Using Virtual Environments to Improve Real-World Motor Skills in Sports: A Systematic Review," Frontiers in Psychology, vol. 10, p. 2159, Sep. 2019, doi: 10.3389/fpsyg.2019.02159.
33. Rebelo, A., Martinho, D. V., Valente-dos-Santos, J., Coelho-e-Silva, M. J., & Teixeira, D. (2023). From data to action: a scoping review of wearable technologies and biomechanical assessments

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

informing injury prevention strategies in sport. BMC Sports Science Medicine and Rehabilitation, 15(1), 169. https://doi.org/10.1186/s13102-023-00783-4

34. Peake, J. M., Kerr, G., & Sullivan, J. P. (2018). A Critical Review of Consumer Wearables, Mobile Applications, and Equipment for Providing Biofeedback, Monitoring Stress, and Sleep in Physically Active Populations. Frontiers in Physiology, 9, 743. https://doi.org/10.3389/fphys.2018.00743
35. Waśkiewicz?, Z., Słomka, K. J., Grzywacz, T., & Juras, G. (2025). Ethical Bias in AI-Driven Injury Prediction in Sport: A Narrative Review of Athlete Health Data, Autonomy and Governance. AI, 6(11), 283. https://doi.org/10.3390/ai6110283
36. Oonk, A., Kempe, M., Lemmink, K., & Buurke, T. J. W. (2025). Examining the concurrent validity of markerless motion capture in dual-athlete team sports movements. Journal of Sports Sciences, 1–12. https://doi.org/10.1080/02640414.2025.2497678
37. Migliaccio, G. M., Padulo, J., & Russo, L. (2024). The Impact of Wearable Technologies on Marginal Gains in Sports Performance: An Integrative Overview on Advances in Sports, Exercise, and Health. Applied Sciences, 14(15), 6649. https://doi.org/10.3390/app14156649
38. Robertson, S., Kremer, P., Aisbett, B., Tran, J. & Cerin, E. (2017). Consensus on measurement properties and feasibility of performance tests for the exercise and sport sciences: a Delphi study. Sports Medicine - Open 3. https://doi.org/10.1186/s40798-016-0071-y