Analele Universităţii din Oradea
Facicula Educaţie Fizică şi Sport
ISSN **2286-2870**, E-ISSN **1224-5100**

XXXVI / 2026, pp. 45-54
DOI 10.30892/AUOFEFS.2026.05

ARTIFICIAL INTELLIGENCE IN SPORTS PERFORMANCE AND COACHING: CURRENT APPLICATIONS AND EMERGING CHALLENGES

Stefan ALECU [1*]

1. Department of Physical education and special motricity, Faculty of Physical education and mountain sports, Transilvania University of Brașov.

* *Corresponding author: Stefan ALECU, e-mail: alecu.stefan@unitbv.ro*

Citation: Alecu S. (2026). Artificial intelligence in sports performance and coaching: current applications and emerging challenges. *Analele Universităţii din Oradea. Fascicula Educaţie Fizică şi Sport, XXXVI*, pp. 45–54. https://doi.org/10.30892/AUOFEFS.2026.05

Abstract: Artificial intelligence is increasingly used to transform athlete data into predictions, classifications, and decision-support outputs for coaches and sport scientists. This review examines current applications of machine learning, deep learning, computer vision, and generative artificial intelligence in sports performance and coaching. A structured narrative approach was used to synthesize peer-reviewed research published mainly between 2018 and 2026, with emphasis on athlete monitoring, training individualization, technical and tactical analysis, injury-risk estimation, talent identification, and coach learning. The evidence shows that artificial intelligence can automate movement recognition, combine high-frequency wearable and tracking data, identify non-linear performance patterns, and improve the speed of video and match analysis. However, predictive accuracy reported in experimental studies does not automatically translate into effective coaching decisions. Small samples, class imbalance, inconsistent outcome definitions, limited external validation, data leakage, poor calibration, and low model explainability remain frequent problems. Generative tools can support planning, report preparation, and reflective practice, but their outputs require verification because they may omit context or generate inaccurate recommendations. The most appropriate role of artificial intelligence is therefore decision support rather than autonomous decision-making. Practical implementation should begin with a clear coaching question, validated data, interpretable outputs, and continuous human oversight. Future research should prioritize multicenter validation, female and youth athlete representation, sport-specific benchmarks, transparent reporting, and prospective studies that measure whether AI-supported decisions improve performance, health, and coaching efficiency.

Key words: artificial intelligence, machine learning, sports performance, coaching, athlete monitoring, computer vision, injury prediction.

* * * * * *

INTRODUCTION

Modern sport produces large and diverse datasets. Global navigation satellite systems, inertial sensors, heart-rate monitors, force platforms, video systems, wellness questionnaires, and competition databases can describe an athlete from several perspectives. The practical problem is no longer limited to collecting information. Coaches must identify which information is reliable, relevant, and actionable within a short decision window. Artificial intelligence (AI) offers methods for detecting patterns that are difficult to identify through manual review or conventional summary statistics.

AI is an umbrella term that includes machine learning, deep learning, computer vision, natural language processing, optimization, and generative models. In sports practice, machine learning is often used to predict a continuous outcome, classify an athlete or event, detect clusters, or rank alternatives. Deep learning is especially relevant when the input consists of images, video, audio, or long time series. Generative AI can create or transform text, images, and analytical summaries, which has introduced new possibilities for coach education and workflow support. The scientific literature has expanded quickly. Claudino et al. (2019) identified 58 studies using 11 AI techniques across 12 team sports, but the pooled sample was strongly dominated by male athletes. Later reviews confirmed that football receives a disproportionate share of research attention and that tree-based models, support vector machines, and neural networks are common methods (Rico-González et al., 2023; Munoz-Macho et al., 2024). These findings show technical progress, but they also reveal an evidence base concentrated in a limited number of sports and populations. A 2026 scoping review mapped 270 peer-reviewed studies and confirmed that action recognition, injury prediction, and talent identification are leading application areas, while usability and interpretability remain major research gaps (Cattle et al., 2026).

The key question for coaches is not whether an algorithm can produce an accurate result in one dataset. The key question is whether the result remains valid for a new athlete, team, season, or competition context and whether it changes a decision in a beneficial way. This distinction is important because sport performance emerges from interacting physical, technical, tactical, psychological, environmental, and organizational factors. An accurate model can still be impractical if it produces information too late, uses unavailable variables, or gives outputs that the coaching staff cannot interpret. The purpose of this review is to examine the main applications of AI in sports performance and coaching, evaluate their practical value, identify current methodological and ethical limitations, and propose principles for responsible implementation. The focus is on tools that support athlete monitoring, training design, technical and tactical analysis, health management, talent development, and coach learning.

MATERIALS AND METHODS

A structured narrative review design was selected because the topic includes heterogeneous technologies, sports, outcomes, and study designs. The review followed recommendations for transparent narrative synthesis and incorporated elements of systematic searching to reduce selective coverage (Ferrari, 2015). Search concepts combined terms related to artificial intelligence with terms related to sport performance and coaching. A representative search string was: “artificial intelligence” OR “machine learning” OR “deep learning” OR “computer vision” OR “generative AI”, AND “sport” OR “athlete”, AND “performance” OR “coaching” OR “training” OR “injury” OR “tactical analysis”. The syntax was adapted to the requirements of each database. The target sources included PubMed, Scopus, Web of Science, SPORTDiscus, and IEEE Xplore, supplemented by reference-list screening. Searches were completed in July 2026. Systematic reviews, validation studies, and peer-reviewed original research were prioritized when available. Priority was given to peer-reviewed articles published from January 2018 to July 2026, while earlier methodological sources were retained when necessary.

Study selection was conducted by the author through title and abstract screening followed by full-text review; publications of uncertain relevance were resolved at the full-text stage, and only English-language publications were included. Eligible publications examined AI methods in competitive or developmental sport and reported applications relevant to performance, coaching, athlete health, movement analysis, or decision support. Reviews, observational studies, validation studies, and applied methodological papers were considered. Studies focused only on betting, spectator marketing, broadcasting, or general physical activity without a clear coaching or athlete-performance application were excluded. The final thematic synthesis included 21 sport-related AI publications. The six domains were established during narrative synthesis based on recurring application areas in the included literature. Evidence was synthesized into six practical domains: monitoring and individualization, technical and biomechanical analysis, tactical analysis, injury and health support, talent development, and generative AI for coaching.

RESULTS

Athlete monitoring and training individualization

Wearable and tracking systems provide the main data foundation for AI-supported athlete monitoring. Common inputs include total distance, high-speed running, accelerations, impacts, heart rate, heart-rate variability, sleep, session rating of perceived exertion, wellness, and neuromuscular test results. Wearables can collect these measures repeatedly under ecological conditions, but the value of the system depends on sensor validity, standardized procedures, and athlete adherence (Seshadri et al., 2019).

Machine-learning models can combine internal and external load variables and identify individual response patterns. In practice, a model may estimate perceived exertion, detect atypical fatigue, classify training intensity, or forecast readiness for a planned session. This is useful when the coaching staff must evaluate many athletes and multiple indicators each day. Haller et al. (2023), for example, demonstrated how a multidimensional monitoring approach could integrate load, wellness, blood, and strength-related measures in elite youth football. The study also illustrated the difficulty of generating stable injury and illness predictions from short monitoring periods and relatively small samples. The strongest practical use is often descriptive or diagnostic rather than fully predictive. AI can flag unusual changes, group similar response profiles, and show which variables contributed most to a result. Coaches can then compare the alert with contextual information such as travel, illness, tactical role, menstrual cycle, training phase, and recent competition exposure. This human interpretation prevents the model from converting normal variation into unnecessary training restrictions.

Table 1. Main applications of artificial intelligence in sports performance and coaching

Application	Typical data	Common methods	Coaching output	Main limitation
Monitoring and individualization	GPS/GNSS, IMU, heart rate, HRV, wellness, sleep	Random forest, XGBoost, neural networks, clustering	Readiness flags, load profiles, individualized targets	Device error, missing data, athlete-specific variability
Technical and biomechanical analysis	Video, depth cameras, joint coordinates, force data	Pose estimation, convolutional networks, time-series models	Technique feedback, movement classification, automated tagging	Occlusion, calibration, task-specific validity
Tactical and match analysis	Player tracking, event data, ball position, contextual variables	Clustering, sequence models, graph methods, classification	Pattern detection, opponent analysis, scenario comparison	Context dependence and weak transfer between teams
Injury and health support	Training load, injury history, screening, wellness, exposure	Classification, survival models, ensemble learning	Risk alerts, prioritization for clinical review	Rare outcomes, class imbalance, poor external validation
Talent and	Testing, match actions,	Ranking, classification,	Development profiles	Selection bias and

player development	growth, anthropometry, learning history	regression, representation learning	and recruitment support	unstable youth development pathways
Generative AI and coach learning	Reports, transcripts, plans, video notes, scientific text	Large language models and natural language processing	Summaries, reflective questions, draft plans, communication support	Inaccurate content, privacy risks, loss of context

Technical and biomechanical analysis

Computer vision can automate tasks that previously required manual coding or laboratory motion-capture systems. Deep-learning models can identify athletes, estimate body landmarks, classify sport-specific actions, and segment technical phases. Cust et al. (2019) reviewed 52 studies on sport-specific movement recognition and showed that both inertial-sensor and vision-based approaches can produce high classification performance, although preprocessing, validation, and model reporting varied substantially. Markerless motion capture has increased access to biomechanical analysis. Commercial cameras and open-source pose-estimation systems can estimate two-dimensional or three-dimensional joint positions without reflective markers. Recent evidence shows useful reliability for several controlled movements, while errors differ by joint, movement plane, camera setup, and occlusion conditions (Auer et al., 2024; Edriss et al., 2025). Lichtwark et al. (2024) also showed that whole-body markerless motion data can support prediction of ground-reaction forces across walking, running, jumping, and cutting tasks.

For coaching, the main advantage is speed. Video can be converted into joint-angle traces, event counts, or movement-quality indicators soon after a session. The main risk is false precision. A system may display a joint angle to one decimal place even when the underlying error is several degrees. Coaches should therefore use validated variables, confidence intervals or error bands, and repeated observations rather than interpreting a single automatically generated value as a definitive technical diagnosis.

Tactical analysis and competition decision support

Tracking and event data allow AI systems to describe spatial organization, pressing behavior, passing options, team compactness, and transitions. In football, large datasets have encouraged methods that integrate sport science, computer science, and tactical expertise. Goes et al. (2021) emphasized that useful tactical analysis depends on feature construction and contextual interpretation, not only on model selection. The same numerical pattern may have a different meaning depending on score, opponent quality, player role, match phase, and tactical intention. AI can support opponent analysis by automatically tagging events, retrieving similar situations, and ranking patterns that precede successful or unsuccessful outcomes. Predictive models can also estimate match results or possession outcomes, but prediction alone provides limited coaching value unless the model identifies controllable variables (Bunker & Thabtah, 2019). A coach benefits more from knowing which spacing or decision pattern is associated with a higher probability of success than from receiving a final win probability without explanation. The most promising systems use an interactive workflow. Analysts define the tactical question, the model searches large datasets, and coaches evaluate the output against video and game principles. This arrangement maintains domain expertise and reduces the risk that correlations are mistaken for tactical causes.

Injury-risk estimation and athlete health

Injury prediction is one of the most visible AI applications in sport, but it is also one of the most difficult. Injuries are relatively rare, definitions differ, exposure changes over time, and risk factors interact dynamically. Van Eetvelde et al. (2021) reported predictive performance ranging from weak to strong across included studies, with area-under-the-curve values from approximately 0.52 to 0.87. This wide range reflects differences in samples, injury definitions, preprocessing, validation, and outcome imbalance. Some applied studies demonstrate useful possibilities. Rossi et al. (2018) used GPS-derived training data to develop an interpretable injury-forecasting approach in professional football. Such work shows how workload patterns can contribute to screening. However, a risk score does not establish that a specific training exposure caused an injury, and it does not determine the correct intervention.

Methodological reviews advise caution. Bullock et al. (2022) evaluated 204 prediction models from 30 studies and found that most had high or unclear risk of bias, while none had undergone external validation. Nassis et al. (2023) similarly concluded that machine learning may help identify early signs of elevated risk but does not yet provide consistently high predictive ability for routine injury prevention. The appropriate output is therefore a risk signal for multidisciplinary review, not an automated decision to rest, select, or medically clear an athlete.

Talent identification and long-term development

AI can integrate technical actions, physical tests, anthropometry, maturation, and competition data to profile players or identify development pathways. These tools can reduce the time needed to review large athlete pools and can highlight individuals whose strengths are not captured by a single test. They can also support individualized development by comparing an athlete with age-, role-, or stage-specific reference profiles.

The main limitation is that talent labels are shaped by previous selection systems. A model trained on athletes already chosen by academies may reproduce preferences for early maturation, current size, access to training, or specific playing styles. Youth development is also non-linear. Ranking a young athlete with a single probability may create unjustified certainty and influence opportunities. AI should support repeated developmental assessment, while final decisions should include coach observation, growth status, learning behavior, motivation, and environmental context.

Generative artificial intelligence and coach learning

Large language models can draft session plans, summarize research, translate reports, generate reflective questions, organize observation notes, and adapt communication for different audiences. They may reduce administrative workload and help coaches explore alternatives. O'Brien and Prentice (2025) demonstrated an early application of freely available GPT tools to analyze coach-athlete dialogue using a predefined framework.

These systems generate plausible language rather than verified sport-science conclusions. They may invent references, ignore contraindications, or produce generic training recommendations without understanding the athlete. Sensitive athlete data also creates privacy and governance concerns when uploaded to public systems. Coaches should use generative AI for low-risk support tasks, remove identifying information, specify the performance context, request evidence, and verify every recommendation against qualified professional judgment.

Emerging Challenges

Data quality is the first constraint. AI cannot correct inconsistent injury coding, changing sensor placement, missing sessions, weak test reliability, or unclear outcome definitions. Larger datasets are useful only when measurements remain comparable. Sport organizations should establish data dictionaries, device protocols, quality checks, and clear ownership before developing predictive models. Generalizability is the second constraint. Models often learn team-specific routines, competition structures, or device characteristics. Performance can fall when the model is transferred to a new club, age group, sex, playing level, or season. External validation and prospective testing are therefore essential. This requirement is especially important because current evidence overrepresents male football populations (Claudino et al., 2019; Munoz-Macho et al., 2024).

Explainability and calibration affect adoption. Coaches need to know why a model generated an alert, how uncertain the prediction is, and what action remains under their control. A system that is slightly less accurate but transparent may be more useful than a black-box model with a small statistical advantage. Hammes et al. (2022) and Sperlich et al. (2023) identify explainability, practitioner control, and reliable data as central conditions for successful AI use in elite sport. AI also changes roles within sport-science teams. Automated reporting may free time for interpretation and athlete contact, but poorly designed automation can increase complexity, reduce skill, and create overdependence. Naughton et al. (2024) argue that AI implementation should be treated as a sociotechnical change involving people, tasks, technologies, and organizational structures. Training for coaches and staff should therefore include data literacy, model limitations, privacy, and procedures for challenging an automated output.

Table 2. Implementation risks and practical safeguards

Risk	Possible consequence	Recommended safeguard
Data leakage or overfitting	High internal accuracy that fails in a new season or team	Separate training and test data by athlete and time; use external validation
Class imbalance	The model misses rare injuries while reporting acceptable overall accuracy	Report sensitivity, specificity, precision, calibration, and decision thresholds
Black-box output	Coaches cannot judge whether the result is reasonable	Use feature explanations, uncertainty estimates, and case-based visualizations
Biased training data	Lower validity for female, youth, lower-resource, or less-studied sports	Audit subgroup performance and expand representative datasets
Automation bias	Staff follow the model despite contradictory clinical or coaching evidence	Require human review and document the final decision rationale
Privacy and ownership gaps	Unauthorized use of health, video, or performance data	Use access controls, de-identification, retention rules, and informed governance

Evaluating Model Performance and Practical Utility

AI studies in sport frequently report accuracy, but accuracy alone can be misleading. When an outcome is rare, a model can achieve a high accuracy by predicting the majority class for almost every case. Injury-risk models should therefore report sensitivity, specificity, positive predictive value, negative predictive value, area under the receiver operating characteristic curve, and calibration. For continuous outcomes, mean absolute error and root mean square error should be interpreted against the normal measurement error and the smallest change that would influence a coaching decision.

Data separation is another critical issue. Randomly dividing individual observations can place sessions from the same athlete in both the training and test sets. The model may then recognize athlete-specific patterns rather than learn a general relationship. A stronger evaluation separates data by athlete, team, and time. A model intended for future decisions should be tested on a later period, while a model intended for transfer should be tested in an independent team or competition. Preprocessing, feature selection, and hyperparameter tuning must be performed only within the training data to prevent data leakage. Model comparison should include simple baselines. Complex algorithms do not automatically outperform logistic regression, linear models, or clear rule-based thresholds. The additional complexity is justified only when it produces a meaningful gain and remains interpretable enough for the intended decision. Bullock et al. (2022) showed that many sport-injury models lacked adequate validation and reporting. This finding supports the use of reporting checklists, open code where possible, and a clear description of missing-data handling, class balancing, feature engineering, and threshold selection.

Calibration is especially important in applied sport. A model is calibrated when athletes assigned a 20% risk experience the outcome at approximately that rate across comparable cases. A model may rank athletes correctly but produce risk probabilities that are too high or too low. Poor calibration can lead to excessive restrictions, missed warnings, and reduced trust. Decision-curve analysis or cost-sensitive evaluation can help determine whether the model offers more value than current practice at a chosen action threshold. The final test is prospective impact. Researchers should examine whether providing the model output changes the coach or clinician decision and whether that change improves an athlete-centered outcome. A dashboard that is statistically accurate but ignored by staff has no operational effect. Conversely, an imperfect model may be useful if it prompts timely discussion and improves consistency. Practical evaluation should measure usability, response time, alert burden, staff agreement, athlete acceptance, and the consequences of incorrect recommendations.

A Practical Workflow for AI-Supported Coaching

An AI project should begin with a clearly defined decision. Examples include selecting the appropriate intensity for the next session, identifying video clips that illustrate a tactical problem, or prioritizing athletes for further medical assessment. The decision should have a responsible owner, a defined time point, and a realistic action. Without this structure, teams often build dashboards that display large amounts of information but do not improve practice. The second stage is data readiness. Staff should identify the minimum variables required, verify that devices and tests are reliable, and establish procedures for missing or implausible values. Data collection should fit the daily routine. A theoretically useful variable is unlikely to help if athletes complete it inconsistently or if the result becomes available after the training decision. Teams with limited resources can begin with a small number of stable measures rather than purchasing multiple systems that create fragmented datasets.

The third stage is model development and validation. The analytical team should define the target outcome before examining results, compare several methods, test simple baselines, and preserve an untouched evaluation dataset. Outputs should be converted into a format the user understands. A coach may need a trend, a traffic-light alert with uncertainty, or a short list of video examples rather than a probability with no context. Each output should also state what the system cannot determine. The fourth stage is a controlled pilot. Coaches should receive the AI output alongside the existing process and record whether it changes their judgment. False alerts, missed cases, and disagreements should be reviewed with the analyst and relevant practitioners. The model may require recalibration when the squad, training plan, competition level, or device changes. Continuous monitoring is necessary because sport environments are not stationary.

The final stage is governance. The organization should define who can access raw and processed data, how long information is retained, whether data can be used for research or commercial purposes, and how athletes can ask questions or withdraw consent where applicable. High-impact decisions should remain reviewable. A documented audit trail should show the model version, input data, output, professional interpretation, and final action.

DISCUSSION

The reviewed literature indicates that AI has moved beyond experimental sport analytics. It now supports automated video analysis, wearable-data interpretation, performance classification, tactical pattern detection, and communication tasks. Recent reviews report broad application across performance and healthcare domains, and meta-analytic work suggests measurable gains in analytical performance for selected tasks (Pietraszewski et al., 2025). However, the maturity of applications differs. Movement recognition and video tagging are closer to operational use because the target event can be directly observed. Injury prediction and long-term talent forecasting remain less stable because the outcomes are infrequent, multifactorial, and context-dependent. A useful distinction is between automation and augmentation. Automation replaces a repetitive task, such as tagging sprints or generating a standard report. Augmentation improves a professional decision by combining information, displaying uncertainty, and offering alternatives. The second function has greater potential for coaching, but it also requires stronger collaboration between data scientists, sport scientists, medical staff, analysts, coaches, and athletes.

The implementation process should start with a decision rather than an algorithm. The staff should define the question, the available action, the acceptable cost of false-positive and false-negative results, and the time at which the output is needed. A simple, interpretable model may be preferable when it answers the question with sufficient accuracy. The model should then be evaluated prospectively against current practice. Relevant outcomes include decision time, staff agreement, athlete adherence, injury burden, performance change, and coach trust, not only classification accuracy. Human oversight remains essential. Coaches provide knowledge about intention, role, environment, and interpersonal factors that are rarely represented in datasets. Athletes also need meaningful involvement because monitoring quality depends on trust and honest reporting. AI should therefore be integrated into a feedback cycle in which data generate a hypothesis, professionals interpret it, an action is selected, and the athlete response is reviewed.

Practical Applications

Define one operational question, such as identifying unusual fatigue before high-intensity training, before collecting additional data.

Validate sensors, labels, and test procedures before comparing machine-learning models.

Use chronological and athlete-level data separation to prevent information from the same athlete or future period entering both training and test sets.

Present predictions with explanations, uncertainty, and a clear action pathway.

Pilot the tool with a small group, compare it with current staff decisions, and monitor errors over time.

Keep medical clearance, selection, and major load-management decisions under qualified human responsibility.

CONCLUSIONS

The Artificial intelligence can improve the speed, scale, and consistency of sports performance analysis. Its most established uses involve automated movement recognition, video processing, athlete monitoring, and the organization of complex datasets. Predictive applications in injury prevention, talent identification, and long-term performance planning remain promising but require stronger validation. Generative AI can support coach learning and administrative work, but it cannot replace contextual judgment or professional responsibility. Effective implementation depends on a clear coaching problem, valid data, transparent models, representative samples, and continuous human oversight. The central objective is not to replace the coach. It is to provide better evidence at the moment a coach must decide.

LIMITATIONS AND FUTURE DIRECTIONS

This review used a narrative synthesis and did not calculate pooled effects across applications. The literature is heterogeneous in sport, sample, data source, outcome definition, and model evaluation, which limits direct comparison. Rapid software development also means that commercial capabilities may change faster than peer-reviewed validation.

Future research should use prospective multicenter designs, preregistered analysis plans, transparent code and model reporting, calibration measures, and external validation. Studies should include female athletes, youth athletes, para-athletes, individual sports, and lower-resource settings. Researchers should also compare AI-supported decisions with normal coaching practice and report whether the technology improves meaningful outcomes. Generative AI requires sport-specific evaluation datasets that test factual accuracy, safety, privacy, and usefulness for different coaching tasks.

REFERENCES

Auer, S., Süß, F., & Dendorfer, S. (2024). Using markerless motion capture and musculoskeletal models: An evaluation of joint kinematics. Technology and Health Care, 32(5), 3433-3442. https://doi.org/10.3233/THC-240202

Bunker, R. P., & Thabtah, F. (2019). A machine learning framework for sport result prediction. Applied Computing and Informatics, 15(1), 27-33. https://doi.org/10.1016/j.aci.2017.09.005

Bullock, G. S., Mylott, J., Hughes, T., Nicholson, K. F., Riley, R. D., & Collins, G. S. (2022). Just how confident can we be in predicting sports injuries? A systematic review of the methodological conduct and performance of existing musculoskeletal injury prediction models in sport. Sports Medicine, 52(10), 2469-2482. https://doi.org/10.1007/s40279-022-01698-9

Cattle, A., Johnston, K., McAuley, A. B. T., Kelly, A., & Baker, J. (2026). Machine learning applications in sport: A scoping review. Frontiers in Psychology, 17, 1802549. https://doi.org/10.3389/fpsyg.2026.1802549

Claudino, J. G., Capanema, D. O., de Souza, T. V., Serrão, J. C., Pereira, A. C. M., & Nassis, G. P. (2019). Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: A systematic review. Sports Medicine - Open, 5, 28. https://doi.org/10.1186/s40798-019-0202-3

Cust, E. E., Sweeting, A. J., Ball, K., & Robertson, S. (2019). Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance. Journal of Sports Sciences, 37(5), 568-600. https://doi.org/10.1080/02640414.2018.1521769

Edriss, S., Romagnoli, C., Caprioli, L., Bonaiuto, V., Padua, E., & Annino, G. (2025). Commercial vision sensors and AI-based pose estimation frameworks for markerless motion analysis in sports and exercises: A mini review. Frontiers in Physiology, 16, 1649330. https://doi.org/10.3389/fphys.2025.1649330

Ferrari, R. (2015). Writing narrative style literature reviews. Medical Writing, 24(4), 230-235. https://doi.org/10.1179/2047480615Z.000000000329

Goes, F. R., Meerhoff, L. A., Bueno, M. J. O., Rodrigues, D. M., Moura, F. A., Brink, M. S., Elferink-Gemser, M. T., Knobbe, A. J., Cunha, S. A., Torres, R. S., & Lemmink, K. A. P. M. (2021). Unlocking the potential of big data to support tactical performance analysis in professional soccer: A systematic review. European Journal of Sport Science, 21(4), 481-496. https://doi.org/10.1080/17461391.2020.1747552

Haller, N., Kranzinger, S., Kranzinger, C., Blumkaitis, J. C., Strepp, T., Simon, P., Tomaskovic, A., O'Brien, J., Düring, M., & Stöggl, T. (2023). Predicting injury and illness with machine learning in elite youth soccer: A comprehensive monitoring approach over 3 months. Journal of Sports Science and Medicine, 22(3), 476-487. https://doi.org/10.52082/jssm.2023.476

Hammes, F., Hagg, A., Asteroth, A., & Link, D. (2022). Artificial intelligence in elite sports: A narrative review of success stories and challenges. Frontiers in Sports and Active Living, 4, 861466. https://doi.org/10.3389/fspor.2022.861466

Lichtwark, G. A., Schuster, R. W., Kelly, L. A., Trost, S. G., & Bialkowski, A. (2024). Markerless motion capture provides accurate predictions of ground reaction forces across a range of movement tasks. Journal of Biomechanics, 166, 112051. https://doi.org/10.1016/j.jbiomech.2024.112051

Munoz-Macho, A. A., Domínguez-Morales, M. J., & Sevillano-Ramos, J. L. (2024). Performance and healthcare analysis in elite sports teams using artificial intelligence: A scoping review. Frontiers in Sports and Active Living, 6, 1383723. https://doi.org/10.3389/fspor.2024.1383723

Nassis, G. P., Verhagen, E., Brito, J., Figueiredo, P., & Krustrup, P. (2023). A review of machine learning applications in soccer with an emphasis on injury risk. Biology of Sport, 40(1), 233-239. https://doi.org/10.5114/biolsport.2023.114283

Naughton, M., Salmon, P. M., Compton, H. R., & McLean, S. (2024). Challenges and opportunities of artificial intelligence implementation within sports science and sports medicine teams. Frontiers in Sports and Active Living, 6, 1332427. https://doi.org/10.3389/fspor.2024.1332427

O'Brien, K. A., & Prentice, S. (2025). Assessing the practicality of using freely available AI-based GPT tools for coach learning and athlete development. Frontiers in Sports and Active Living, 7, 1627685. https://doi.org/10.3389/fspor.2025.1627685

Pietraszewski, P., Terbalyan, A., Roczniok, R., Maszczyk, A., Ornowski, K., Manilewska, D., Kuliś, S., Zając, A., & Gołaś, A. (2025). The role of artificial intelligence in sports analytics: A systematic review and meta-analysis of performance trends. Applied Sciences, 15(13), 7254. https://doi.org/10.3390/app15137254

Rico-González, M., Pino-Ortega, J., Méndez, A., Clemente, F. M., & Baca, A. (2023). Machine learning application in soccer: A systematic review. Biology of Sport, 40(1), 249-263. https://doi.org/10.5114/biolsport.2023.112970

Rossi, A., Pappalardo, L., Cintia, P., Iaia, F. M., Fernàndez, J., & Medina, D. (2018). Effective injury forecasting in soccer with GPS training data and machine learning. PLOS ONE, 13(7), e0201264. https://doi.org/10.1371/journal.pone.0201264

Seshadri, D. R., Li, R. T., Voos, J. E., Rowbottom, J. R., Alfes, C. M., Zorman, C. A., & Drummond, C. K. (2019). Wearable sensors for monitoring the internal and external workload of the athlete. npj Digital Medicine, 2, 71. https://doi.org/10.1038/s41746-019-0149-2

Sperlich, B., Düking, P., Leppich, R., & Holmberg, H.-C. (2023). Strengths, weaknesses, opportunities, and threats associated with the application of artificial intelligence in connection with sport research, coaching, and optimization of athletic performance: A brief SWOT analysis. Frontiers in Sports and Active Living, 5, 1258562. https://doi.org/10.3389/fspor.2023.1258562

Van Eetvelde, H., Mendonça, L. D., Ley, C., Seil, R., & Tischer, T. (2021). Machine learning methods in sport injury prediction and prevention: A systematic review. Journal of Experimental Orthopaedics, 8, 27. https://doi.org/10.1186/s40634-021-00346-x

Submitted:	Revised:	Accepted and published online
July 22, 2026	August 25, 2026	September 07, 2026