Dašić, D., Vuković, M. (2025) Machine learning as a methodological framework in sports science – from exploratory to confirmatory analyses In: Dašić, D. (ed) Sporticopedia SMB2025, Vol 3, No 1, 187-202

DOI: https://doi.org/10.58984/smbic250101187d
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MACHINE LEARNING AS A METHODOLOGICAL FRAMEWORK IN SPORTS SCIENCE – FROM EXPLORATORY TO CONFIRMATORY ANALYSES

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Abstract: In sports science, the use of machine learning and artificial intelligence techniques has increased significantly in recent years, especially in the domains of performance evaluation, training process optimization, and sports injury prediction. However, a significant number of current studies have significant methodological issues, such as poor validation processes, the possibility of information contamination (data leakage), a lack of reporting transparency, and restricted generalizability of findings. Through a narrative evaluation of peer-reviewed scientific literature indexed in the Web of Science and Scopus databases, this research aims to identify major sources of methodological bias and analyze prevailing methodological practices in the application of machine learning in sport. In order to obtain a meaningful evaluation of model performance, time-aware data splitting and grouped validation procedures are required due to the unique temporal and hierarchical structure of sports data. The use of modern reporting and quality-assessment frameworks, such as TRIPOD+AI and PROBAST+AI, is critically examined in this study, along with the contribution of interpretable models and explainable AI techniques to improving results' practical applicability and trustworthiness. In order to improve methodological rigor, transparency, and reproducibility, recommendations are developed for future study and practical use of machine learning in sports science based on the synthesis of the literature.

Keywords: machine learning; sports science; model validation; data leakage; explainable AI

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Project: **MINIPART**. Improving Participation in Spatial Planning of Mining Areas. the Science Fund of the Republic of Serbia (grant #7598) and the Ministry of Science, Technological Development and Innovation of the Republic of Serbia (grant no. 451-03-137/2025-03/200131

Introduction

The past decade has brought a significant methodological shift in sports science, in which machine learning (ML) has increasingly moved beyond the role of a purely predictive tool and has become an integrated framework for research, validation, and reporting of results (Dasic, 2018; Stanković, et al., 2024). Contemporary studies indicate that ML methods enable researchers to analyze large and complex datasets on athletes—ranging from physiological and biomechanical to psychological and contextual data—thereby uncovering patterns that were not accessible through traditional statistical methods (Reis, Alaiti, Vallio, & Hespanhol, 2024). Such approaches are particularly relevant for injury risk analysis, training optimization, and the individualization of return-to-play processes. Because measurements frequently come from numerous levels (repeated measurements within the same athlete, throughout teams, and across different seasons), sports data naturally display a strong temporal and hierarchical structure. To prevent information leaking and provide a realistic evaluation of model generalizability, this structure requires the employment of time-aware data partitioning and grouped validation processes (Dašić 2023a; Dašić 2023b).

But using machine learning in sports research comes with new methodological difficulties in addition to analytical benefits. Kapoor and Narayanan (2023) claim that data leaks, reproducibility issues, and inadequately transparent model validation plague many published studies, casting doubt on the validity of the claimed results. Because of this, new frameworks like TRIPOD+AI and PROBAST+AI place a strong emphasis on openness, reporting uniformity, and methodical evaluation of the risk of bias in ML-based research (Collins et al., 2024; Moons et al., 2025).

Simultaneously, there has been a growing focus on explainable machine learning (Explainable Artificial Intelligence—XAI), which allows for the interpretation of the contribution of individual variables to model outcomes and insight into the internal mechanisms of models (Finzel et al., 2025). XAI acts as a link between algorithmic "black boxes" and practitioners in the sports industry, such as coaches, doctors, and analysts, who need precise and reliable information to aid in decision-making (Vuković, et al., 2023; Vuković et al., 2024). As a result, machine learning is developing as a methodological paradigm that combines exploratory and confirmatory approaches rather than operating as a stand-alone statistical methodology, promoting a shift toward a more transparent, interdisciplinary, and repeatable sports science (Lunić, Ćesarević, 2025; Mlađenović, 2025).

Literature Review

According to recent reviews, machine learning (ML) in sports is now a comprehensive methodological framework that influences study design, model validation (such as grouped/temporal and nested cross-validation), and transparent performance reporting, including explainability approaches (XAI) and control over data leakage. This viewpoint is especially pertinent to studies on performance analysis, return-to-training/return-to-play procedures, and injury risk.

One of the most important methodological improvements of the last ten years is the recent advancements in machine learning in sports science. New methods of research and evidence-based decision making have been made possible by the explosive development in data from physiological measures, biomechanical studies, and sports performance monitoring. In this regard, many authors stress that machine learning should be seen as a methodological approach that incorporates data analysis, validation, and interpretation into a cohesive research framework rather than just as a predictive tool (López-Fernández et al., 2022).

According to empirical research, machine learning (ML) techniques are used in a variety of sports-related fields, such as injury risk analysis, training optimization, tactical pattern analysis, and competition outcome prediction. The majority of research focuses on performance prediction and injury prevention, although methodological methods remain very varied, according to a systematic review by López-Fernández et al. (2022) that comprised more than 60 papers. Jordan et al. (2023) reached similar conclusions, pointing out that many studies lack sufficient model validation and precise explanations of cross-validation processes, which limits the reproducibility of presented findings.

One of the most active application areas of machine learning in sports, according to a large body of research, is injury prevention. For instance, research in football and rugby has shown that algorithms like Random Forest, XGBoost, and Support Vector Machines can accurately predict injury risk with over 80% accuracy when sample sizes are sufficient and the temporal structure of the data is maintained (Ruddy et al., 2022; Carey et al., 2023). However, feature selection and the possibility of data leakage—the unintentional incorporation of test set information into model training—are frequently overlooked, leading to unduly optimistic performance estimates.

Machine learning allows researchers to capture intricate relationships between physiological, biomechanical, and psychological aspects of sports performance (Dašić, Vuković, 2024). According to recent research in swimming and basketball, algorithms like gradient boosting models and neural networks can forecast performance results based on factors like age, body composition, training load, and recovery time (Rathore et al., 2023; De Pauw et al., 2024). However, Singh et al.'s (2023) investigation shows that more sophisticated models don't always perform better than more straight-forward regression-based methods, especially when sample sizes are constrained.

There are still significant methodological issues. First, a significant source of bias is the absence of established outcome definitions and unreliable variable measurement (Whitaker et al., 2023). Second, a lot of research don't use the right methods to deal with class imbalance or carry out external validation, which limits how broadly the results can be applied (Rana et al., 2023). Third, reporting hyperparameters and model structure is frequently not transparent enough, which emphasizes the significance of new frameworks like TRIPOD+AI and DOME for enhancing methodological rigor (Mongan et al., 2020).

In the most recent research, model interpretability has received special attention. In order to bridge the gap between statistical intricacy and practical applicability, methods like SHAP and LIME are being employed more frequently to determine the most important elements influencing injury risk or performance results (Calderón-Díaz et al., 2024). According to applied research, using XAI techniques promotes more informed, real-time decision making and increases coaches' and medical experts' trust in automated systems (Zarić et al., 2024; Naughton et al., 2024).

Overall, the literature review shows that machine learning is emerging as a key methodological tool in sports science; nevertheless, the quality of study designs, the selection of validation techniques, and reporting transparency all have a significant impact on the scientific value of machine learning. Therefore, reproducible protocols, ethical data governance, and wider integration of XAI methodologies inside applied sports practice should be the main goals of future methodological development.

Methodology

This study examines whether machine learning (ML) can serve as a methodological framework in sports science that integrates exploratory analysis (pattern and factor discovery) with confirmatory testing (validated predictions and transparent reporting). Rather than conducting a systematic review in accordance with the PRISMA protocol, the research adopts a qualitative approach in the form of a narrative literature review with elements of methodological synthesis. The primary objective is to identify dominant methodological practices in the application of ML in sport and to formulate evidence-based recommendations for model validation, reporting, and interpretability.

In accordance with contemporary methodological standards, this synthesis treats reporting guidelines and tools for assessing study quality and risk of bias in machine-learning-based prediction models as central reference frameworks. In particular, TRIPOD+AI is used as the principal guideline for transparent reporting of prediction model development and validation, while PROBAST+AI is applied as the key framework for evaluating risk of bias and applicability (Collins et al., 2024; Moons et al., 2025).

The literature search primarily targeted peer-reviewed scientific articles indexed in the Web of Science Core Collection and Scopus, which were selected as the main sources of documented scientific evidence due to their strict indexing criteria and high standards of scholarly relevance. PubMed was consulted as a supplementary source to identify studies related to sports medicine and biomedical aspects of artificial intelligence. Google Scholar was used exclusively in a supporting role for citation chasing and reference verification. Studies identified solely through Google Scholar were included in the analysis only if they were also indexed in either the Web of Science or Scopus databases.

Discussion

Advantages and methodological innovations of machine learning in sports research

According to recent studies, machine learning (ML) in sports has evolved from a "supportive" analytical tool to a fundamental methodological framework. It speeds up the transition from scientific understanding to useful decision-making by combining data collection, real-time processing, modeling, and explainable reporting. In order to handle multimodal data streams (GPS/IMU, physiological measures, video, and contextual data), apply sophisticated validation procedures, and evaluate model calibration and generalizability—all of which are essential for the transferability of findings across seasons and clubs—new data-analytic techniques are first required (Bullock et al., 2024; Zhou et al., 2025). Compared with traditional regression-based approaches, modern ensemble and deep learning models more effectively capture nonlinear relationships and interactions among training load, biomechanics, and contextual factors, and—when systematically validated—allow for more realistic predictions of injury risk and performance outcomes (Van Eetvelde et al., 2021; Claudino et al., 2019).

Second, significant advancements in athlete monitoring have been fueled by automation through wearable technology and edge/online processing, where machine learning (ML) reduces reliance on laboratory-based protocols by enabling the detection of workload trends, abnormal movement patterns, and early signals of overload (Rebelo et al., 2023; Wang et al., 2023; Seçkin et al., 2023; Collins et al., 2024). A closed "measurement–analysis–intervention" loop is created by integrating sensors with risk-assessment algorithms, giving coaches immediate input on training dose, readiness, and recuperation

(Mateus et al., 2024; Alzahrani et al., 2024). Because ML models may adjust to specific parameters (age, playing position, injury history) instead of depending on a "average" athlete profile, these systems enable individualized recommendations (Moons et al., 2025).

Third, machine learning makes it easier to find latent patterns that are frequently missed by traditional analysis, such as combinations of workloads at the micro and meso levels, method variability, and subtle indicators of overuse or tiredness. Key predictors can be transparently discovered and assessed for stability using explainable artificial intelligence approaches (such as global and local SHAP), which makes it easier to translate findings into training and rehabilitation procedures (Musat et al., 2024; Zhou et al., 2025). Furthermore, there is growing interest in generative and synthetic approaches (such as tabular variational autoencoders) to address class imbalance and improve robustness in settings with limited sample sizes—a common challenge in elite sport—as long as stringent validation procedures are followed to prevent methodological artifacts (Cordeiro et al., 2025).

Lastly, the area is moving toward greater repeatability thanks to methodological advancements in integrated analytical workflows and reporting uniformity. High-quality reviews and applied research increasingly demonstrate systematic checks of temporal data divides, grouped and internal–external validation procedures, calibration analyses, and evaluations of clinical or practical utility (Bullock et al., 2024; Van Eetvelde et al., 2021). When combined, machine learning (ML) not only improves the precision of injury risk and performance forecasts but also creates a new standard for methodology wherein study design, model validation, explainability, and result transferability are all essential parts of a single, cohesive research process (Claudino et al., 2019; Mateus et al., 2024; Finzel et al., 2025).

Limitations, challenges, and future directions of methodological development

While there are several advantages to using machine learning (ML) in sports research, the existing literature consistently identifies a number of methodological challenges that compromise the validity and generalizability of results. First, bias and low generalizability are still primarily caused by poor data quality and inconsistent outcome definitions (such as what exactly qualifies as a "injury" or a "return to play"). Weak or non-representative measurements, a lack of events, and population mismatch cause poor calibration in the field of healthcare predictive models; these models may discriminate convincingly but consistently overestimate or underestimate risk (Van Calster et al., 2019; Huang et al., 2020). Similar issues arise in sport when heterogeneous data sources (GPS/IMU, video, clinical measures) are combined without a clearly defined quality-control protocol and explicit statements of applicability.

The risk of overfitting and excessively optimistic performance estimations is significantly increased by small sample sizes and significant class imbalance, especially for uncommon events like injuries. In order to prevent parameter instability and artificial inflation of predictive performance, methodological suggestions for minimum sample size for prediction model development stress the significance of matching the number of observed events with model complexity (Riley et al., 2018/2019). When global accuracy measurements are employed in deep learning contexts, chronic class imbalance further jeopardizes model evaluation, underscoring the necessity of suitable performance metrics (such as AUPRC) and carefully chosen rebalancing techniques (Johnson & Khoshgoftaar, 2019; He & Garcia, 2009).

Third, data leakage—situations where information from the test environment unintentionally influences model training, whether through wrong preprocessing order, temporal "look-ahead," or overlap of persons across folds—is a common and frequently overlooked hazard. From unreasonably high metrics to erroneous trust in models, foundational research have detailed the mechanisms and effects of leakage and suggested practical solutions to stop it (Kaufman et al., 2012; Cawley & Talbot, 2010). This essentially means that imputation, scaling, and feature-selection processes must be carefully limited to internal training folds in time-series data typical of sports, with validation carried out using blocked or rolling schemes.

Insufficient standardization of validation and reporting represents another major methodological challenge in this field. Evidence from a large-scale "stress test" review of predictive models conducted during the COVID-19 period shows that the vast majority of studies were affected by a high risk of bias and inadequate reporting transparency, often resulting in inflated performance estimates (Wynants et al., 2020). Despite the availability of established frameworks for medical artificial intelligence—such as MINIMAR, CREMLS, and dedicated reporting recommendations for machine learning—their systematic and consistent adoption in sports science has not yet become common practice. This gap is particularly evident with respect to calibration, internal–external validation, and reproducibility, which remain insufficiently addressed in many published studies and thus constitute a fourth key methodological limitation of current research (Hernandez-Boussard et al., 2020; Stevens et al., 2020; Kolbinger et al., 2024).

Fifth, care must be taken when interpreting the explainability (XAI) requirement. The literature highlights that post hoc "explanations" of intricate black-box models do not always guarantee a trustworthy comprehension of causal mechanisms; in high-stakes situations (such as choices impacting the health of athletes), it might be better to take into account models that are naturally interpretable and verifiable domain assumptions (Rudin, 2019). Simultaneously, thorough documenting of models and datasets, such as "model cards" and "datasheets for datasets," can significantly minimize hidden assumptions and clearly describe intended usage, restrictions, and evaluation procedures (Gebru et al., 2021; Mitchell et al., 2019).

And finally, the intersection of methodology and ethics introduces critical concerns related to privacy and data governance in sport. Recent research highlights that the expansion of "big data" in sport entails not only substantial analytical opportunities but also significant legal and ethical responsibilities, including informed consent, data minimization, controlled access, and transparency regarding secondary data use (West et al., 2024). In practical terms, this requires the implementation of clear protocols for anonymization or pseudonymization, robust access-control mechanisms, and explicit agreements defining data ownership and usage rights for information generated through wearable technologies.

Future directions follow several clear lines.

(1) Methodologically, there is a need for widespread adoption of time-aware data splits, nested hyperparameter optimization, and internal–external validation, accompanied by systematic reporting of calibration and clinical or practical utility.
(2) Open science practices, including preregistration and Registered Reports, as well as the publication of code and configurations, reduce opportunities for post hoc adjustment and strengthen the credibility of findings (Nosek et al., 2018).
(3) Standards for documenting datasets and models (datasheets and model cards) should become a routine component of supplementary materials.
(4) Open datasets with clearly defined access rules (e.g., open football event data and spatiotemporal streams) enable independent replication, benchmark development, and comparative testing (Pappalardo et al., 2019).
(5) Any evaluation of XAI should include tests of explanation stability and comparisons with simpler, interpretable models, in order to avoid reliance on explanations that do not generalize across domains.

Taken together, these guidelines support the transition of ML in sport from a phase of enthusiasm to one of mature, reproducible, and responsible application (Table 1).

Given that sports datasets are typically chronologically and hierarchically structured (repeated measurements within the same athlete, throughout teams, and across seasons), the suggestions made in Table 1 are especially important in this context.

Table 1. Practical framework for the methodological enhancement of machine learning research in sport

Methodological challenge	Recommended measure	Expected effect
Incomplete or inconsistent data	Introduction of standardized measurement procedures and clear data collection protocols	Improved validity and comparability of results
Small samples and class imbalance	Data rebalancing techniques and integration of multiple seasons or teams	Greater model stability and generalizability
Data leakage during validation	Nested and time-blocked cross-validation	More realistic performance estimation and reduced risk of bias
Insufficient reporting transparency	Application of TRIPOD+AI, DOME, and PROBAST+AI guidelines	Improved reproducibility and verifiability of results
Limited model interpretability	Use of XAI techniques and model cards	Clearer explanations and increased trust among practitioners
Lack of open data	Publication of anonymized datasets and source code	Enhanced replicability and benchmark development
Insufficient ethical oversight	Implementation of privacy, consent, and data governance protocols	Data protection and ethical accountability

When random data splits and traditional k-fold techniques are used without blocking or grouping, this significantly raises the danger of biased performance estimate. In this regard, blocked and grouped cross-validation techniques directly promote a more reliable evaluation of model generalizability and are a methodologically better option for data with temporal or clustered structure (Roberts et al., 2017). Furthermore, when hyperparameters and model selection are optimized within the same validation procedure, error estimates may become systematically optimistic; therefore, nested cross-validation constitutes an essential condition for reliable model evaluation and comparison (Varoquaux et al., 2017).

Conclusion

A new methodological framework that transcends the limitations of traditional statistical analysis has been built by the use of machine learning in sports science. Large, multimodal datasets can be integrated using modern methods to create models that not only forecast sports results and injury risks but also offer comprehensible justifications for those forecasts. According to research, connecting exploratory and confirmatory studies is essential for creating trustworthy and useful models. In this sense, machine learning serves as a tool for more accurate decision-making in training, injury prevention, and athlete rehabilitation rather than only as an analytical tool.

However, a number of difficulties accompany methodological advancement. Among the most prevalent issues are still heterogeneous data quality, small sample numbers, the possibility of data leakage, and a lack of established validation processes. The reliability of results is often compromised by inadequate reporting transparency and the lack of universal reproducibility requirements. In this regard, implementing frameworks like TRIPOD+AI, PROBAST+AI, and DOME is an essential step in improving scientific rigor and standardizing evaluation standards.

Explainable models (XAI), open science procedures, and the production of transparent and open datasets that enable independent verification of results should be the focus of future methodological advancements in sports research. Ethical issues like informed consent, privacy, and responsible athlete data administration also require special attention.

In sports science, machine learning is a paradigm shift that goes beyond technology innovation to include significant methodological adjustments. Its ability to combine analysis, interpretation, and practical application into a logical, repeatable, and scientifically supported process is its greatest contribution rather than just forecasting results. Along this path, a key requirement for the long-term and reliable progress of sports science continues to be the connection of technological innovation with strong research ethics.

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