REVIEW ARTICLE

Artificial intelligence metrics and performance optimization in professional soccer: a meta-analytic review

Sm Farooque[1ABCDE], Sharina Naorem[1ABCDE], S Premananda Singh[2ABCDE]

[1] *Tripura University, India*

[2] *National Sports University (A Central University), India*

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Abstract

Background and Study Aim The integration of artificial intelligence (AI) and machine learning (ML) in professional soccer has transformed performance analysis. It enables objective quantification of offensive, defensive, and physical parameters. The aim of this meta-analytic review was to evaluate the effectiveness of AI-based metrics, including expected goals (xG), passing efficiency, injury prediction, defensive actions, and physical tracking, in optimizing soccer performance and decision-making.

Material and Methods Following PRISMA guidelines, studies published between 2000 and mid-2025 were retrieved from Scopus, PubMed, and Web of Science. Peer-reviewed empirical studies applying AI/ML models to professional soccer metrics were included. A random-effects meta-analysis was conducted to synthesize classification accuracy and effect sizes (Cohen's d).

Results From 280 identified records, 15 studies met qualitative inclusion criteria, and 10 provided quantitative data. Pooled effect sizes ranged from d = 0.47 to 0.64. The highest effects were observed for physical tracking (d = 0.64) and expected goals (d = 0.61*). Injury prediction, defensive actions, and passing accuracy also showed significant effects (p < .001). AI models achieved an average predictive accuracy of 88% and outperformed traditional analytical methods.

Conclusions AI-driven performance metrics substantially enhance predictive accuracy, tactical evaluation, and injury prevention in soccer. Standardized datasets, explainable models, and longitudinal validation are essential for integrating AI into elite performance management.

Keywords: artificial intelligence, machine learning, soccer performance, expected goals, passing metrics, injury prediction, defensive actions, physical tracking.

Introduction

Performance optimization in professional soccer increasingly relies on advanced statistical metrics derived from game and training data. Among these metrics are expected goals (xG), pass-related metrics, injury prediction, defensive actions, and physical tracking data, which have emerged as core parameters. Each metric quantifies a distinct facet of play and can be modelled using AI/ML methods. Collectively, these indicators form the analytical basis for evaluating match performance, tactical behavior, and physical demands in contemporary professional soccer.

Expected goals is a widely used measure of chance quality. Formally, xG assigns to each shot the probability of resulting in a goal based on contextual features, such as distance, angle, assist type, and defensive pressure. Simpson describes xG as quantifying the likelihood of each shot being scored, providing insight into team and player effectiveness [1]. The importance of xG lies in its ability to isolate shooting quality from scoring randomness. Teams or players may overperform or underperform their xG values, indicating differences in finishing skill or the influence of chance. In practice, xG models are built using supervised learning. Historical shot data, labelled as "goal" or "no goal", are used to train classifiers or regressors, such as logistic regression, gradient boosting, and neural networks, to predict goal probability [2]. This machine learning-based prediction transforms raw event logs into a continuous performance metric. Because xG captures scoring opportunity quality and is strongly associated with team success and match outcomes, it is widely regarded as a principal parameter in performance analysis [3].

Pass-related metrics summarize a team's ball distribution and possession play. Examples include total passes, completion rate, progressive passes, key passes or "expected assists," and measures of passing network structure. These metrics are important because possession and passing patterns underpin most tactical strategies. High pass accuracy and effective passing sequences are associated with game control and chance creation. AI and ML methods are widely applied to passing data. For example, pass origin–destination heatmaps and a k-nearest neighbors model have been used to predict whether a possession will culminate in a shot [4]. Machine learning models have also been

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trained to rate pass quality automatically. A recent study trained classifiers to assign a quality score to each pass and achieved 85% accuracy in matching human expert ratings [5]. More sophisticated models, such as PassAI, integrate multiple data modalities, including player tracking and seasonal statistics, to classify each pass as successful or unsuccessful [6]. These AI-based approaches enable the prediction of pass completion, the identification of key playmakers, and the classification of team passing styles. Accordingly, pass-related metrics represent a central component of performance analysis by capturing essential technical and tactical aspects of play and by allowing machine learning methods to uncover complex passing patterns, such as sequences leading to shots, that are not evident from simple counts [7].

Injury prediction aims to forecast players' injury risk using data on training load, biomechanics, and other factors. This metric is defined as the likelihood that a player will suffer an injury in the near future, based on indicators such as GPS-recorded workloads, acceleration and deceleration counts, and a history of prior injuries. Injury risk is significant because injuries drastically reduce team performance and incur high rehabilitation costs. Rossi emphasizes that injuries "have a great impact on professional soccer" and that clubs lose millions due to player downtime [8]. AI/ML techniques are applied by constructing predictive models, such as decision trees and random forests, trained on historical workload and injury data. For example, Rossi et al. used GPS tracking data from training sessions to build a multidimensional injury forecaster. It accurately predicted injury occurrences and produced interpretable rules linking workload patterns to injury risk [8]. This type of model can alert coaches when a player's load pattern resembles that of a previously injured athlete. Injury prediction is included in this review because it directly affects performance availability. AI-based models for injury prevention are becoming essential tools for optimizing squad fitness and longevity [9].

Defensive actions refer to events such as tackles, interceptions, clearances, blocks, pressures, and duels, as well as their spatial context. Metrics include counts and success rates of these actions, along with advanced values such as "expected defensive threat reduction" (xDEF), which estimate how much a given defensive action decreases the opponent's chance of scoring. These metrics are important because successful defense prevents goals and influences transitions. AI applications include event-based classification and spatial threat modelling. For example, Lamberts (2025) defines xDEF as a probability model that quantifies the likelihood that a given defensive action will reduce the opponent's scoring threat, taking into account player positions and action outcomes [10]. In practice, defenders' actions can be fed into ML models or threat matrices to estimate how much "danger" they remove. Other related metrics, such as those derived from expected possession value frameworks, assign value to defensive events, for example tackles, by measuring changes in expected goals for the opponent [11]. Because most analytics focus on offense, the inclusion of defensive metrics ensures that team defensive strength is also captured. Integrating defensive actions is therefore justified, as AI tools can quantify defensive impact beyond simple counts and contribute to a holistic performance model.

Physical tracking data consist of continuous spatiotemporal measures obtained from GPS or camera systems, including total distance covered, sprint distance, high-speed runs, accelerations and decelerations, positional heatmaps, and physiological loads. These metrics quantify players' physical work rate and intensity. For instance, De Silva notes that GPS data, such as distance and sprints, are "widely used by professional soccer clubs" to profile training and match activity demands [12]. Such data are critical for monitoring fitness, fatigue, and tactical spacing.

Machine learning is applied to tracking data in various ways. For example, ML algorithms, including clustering methods, principal component analysis, and neural networks, have been used to categorize training loads, predict recovery needs, and estimate unobserved variables, such as internal load or readiness, from external metrics. Elliott et al. point out that player tracking allows coaches to monitor whether athletes are adapting to training and to minimize fatigue and injury risk [13]. In performance analysis, ML models can learn typical movement patterns by position or role, detect anomalies, and correlate physical outputs with match outcomes. Since fitness and physical activity are fundamental to performance, the inclusion of tracking metrics enables the physiological dimension of the game to be captured. Together with the other parameters, these tracking measures complete a multifaceted feature set that can be exploited by AI models for comprehensive performance optimization.

Analysis of research findings has shown that the integration of artificial intelligence and machine learning has substantially advanced the quantification and interpretation of technical, tactical, physical, and injury-related aspects of professional soccer performance. Researchers emphasize that AI-based metrics, including expected goals, pass-related indicators, injury risk models, defensive actions, and physical tracking data, provide a more objective and multidimensional understanding of match and training dynamics than traditional descriptive statistics. At the same time, the growing reliance on these data-driven approaches highlights the importance of systematic evaluation of their effectiveness and consistency across different performance domains and competitive contexts. This ongoing need for structured synthesis and comparative assessment logically underpins the focus of the present meta-analytic review on examining how AI-based metrics contribute to performance optimization and decision-making in professional soccer.

Methods

Search Strategy

A comprehensive literature search was performed in PubMed, Scopus, and Web of Science for studies published from January 2000 through mid-2025. Keywords and Boolean combinations included "artificial intelligence", "machine learning", "football" or "soccer", "expected goals", "pass completion", "injury prediction", "player tracking", and related terms. The search followed PRISMA guidelines [14]. References of relevant reviews and articles were hand-searched to identify additional studies. Only peer-reviewed journal articles were considered eligible; conference papers and preprints were excluded to ensure methodological rigor. Studies involving professional or elite soccer players that applied AI/ML techniques to performance metrics were included. Studies focusing on amateur or youth players were included only when the findings were clearly applicable to professional-level performance.

Inclusion and Exclusion Criteria

The inclusion criteria were as follows:

1. Original research published in a peer-reviewed journal between 2000 and 2025 involving AI or ML methods applied to soccer performance metrics.
2. Use of quantitative performance metrics, such as prediction accuracy, AUC, or classification measures, for evaluation within a professional or elite soccer context.
3. Focus on metrics related to expected goals (xG), passes or passing networks, injury risk, defensive actions, and tracking data derived from GPS or inertial systems.
4. Studies not published in English, review articles, technical notes without empirical data, and non-archival reports were excluded.

Data Extraction

The key characteristics of the included studies and the core AI-based performance metrics analyzed in professional soccer are summarized in Table 1. The table provides an overview of the

Table 1. Summary of Core AI-Based Performance Metrics in Professional Soccer (2000–2025)

Metric Name	Definition	Common Data Sources	Typical AI/ML Techniques Applied	Rationale for Inclusion in Meta-Analysis
Expected Goals (xG)	Statistical model estimating the probability of a shot resulting in a goal based on contextual factors, such as distance, angle, assist type, and defensive pressure.	Event-based match logs (Opta, Wyscout, StatsBomb), video tracking data.	Logistic regression, gradient boosting, convolutional neural networks (CNNs), XGBoost, probabilistic models.	xG quantifies offensive efficiency and shot quality and is widely validated as a predictive indicator of team success and finishing ability.
Pass-Related Metrics	Quantitative measures of ball distribution and possession dynamics, including pass completion, progressive passes, key passes, and expected assists (xA).	Event logs, tracking data, video annotation, optical flow systems.	K-nearest neighbors, support vector machines, recurrent neural networks (RNNs), graph neural networks (GNNs).	Passing reflects tactical control, creativity, and build-up efficiency, while AI models can detect playmaking patterns and optimize passing networks.
Injury Prediction	Predictive modelling of injury risk based on external workload metrics and internal load indicators.	GPS tracking, heart rate monitors, biomechanical sensors, training load databases.	Random forests, decision trees, ensemble learning, deep neural networks, Bayesian classifiers.	Injury prevention is essential for sustained performance, and AI enables early detection of overload and risk, improving player availability.
Defensive Actions	Actions preventing scoring opportunities, such as tackles, interceptions, blocks, duels, and clearances, often evaluated through threat reduction models (xDEF).	Event logs, tracking data, positional heatmaps, team defensive databases.	Probabilistic threat modelling, spatiotemporal clustering, reinforcement learning, neural spatial mapping.	Defensive quality strongly correlates with match outcomes, and AI enables the quantification of defensive impact and spatial threat mitigation.

Table 1. Continued.

Metric Name	Definition	Common Data Sources	Typical AI/ML Techniques Applied	Rationale for Inclusion in Meta-Analysis
Physical Tracking Data	Continuous positional and physiological data describing player movement, load, and exertion during training or matches.	GPS, LPS, and optical tracking systems, IMUs (Inertial Measurement Units).	Clustering methods (k-means, DBSCAN), predictive modelling, principal component analysis, deep learning for time-series analysis.	These metrics capture the physical dimension of performance, and AI models transform raw movement data into insights on fitness, fatigue, and tactical intensity.

primary metric categories, their definitions, typical data sources, and analytical approaches reported in studies published between 2000 and 2025. From each eligible study, the following information was extracted: authors, year, sample (teams, players, seasons), data source (e.g., event logs, tracking data), AI/ML methods (algorithms used and feature sets), and key performance outcomes (accuracy, AUC, F1-score, etc.). When available, numerical effect sizes or performance measures, including confidence intervals, were recorded for meta-analysis.

Meta-Analysis

The primary outcome was the classification performance of AI models, assessed using accuracy or area under the curve (AUC), relative to baseline methods. When multiple performance metrics were reported within a study, accuracy or AUC was prioritized. A random-effects model was applied to account for between-study variability. Proportions, such as classification accuracy, were logit-transformed prior to pooling. Forest plots were generated to present pooled estimates with corresponding 95% confidence intervals. Statistical heterogeneity was evaluated using Cochran's Q test and the I^2 statistic, with I^2 values greater than 50% indicating substantial heterogeneity. Subgroup analyses were conducted when data permitted, including comparisons by machine learning approach (traditional versus deep learning) and by metric category. Meta-analytic computations were performed using standard methodological procedures [15].

Results

Study Selection and Characteristics

The process of study identification, screening, eligibility assessment, and final inclusion is illustrated in Figure 1, following the PRISMA 2020 framework.

As presented in Figure 1, a total of 280 records were initially identified through a comprehensive database search conducted across Scopus, PubMed, IEEE Xplore, and Web of Science (n = 256), supplemented by additional records retrieved from Google Scholar, manual reference screening, and cross-citation searches (n = 24). After the removal of duplicate entries, 230 unique studies remained for title and abstract screening. During this stage, 180 records were excluded because they were unrelated to artificial intelligence (AI) applications in soccer performance analysis, theoretical in nature, or not peer-reviewed empirical investigations.

Subsequently, 50 full-text articles were assessed for eligibility based on predefined inclusion criteria encompassing direct relevance to professional soccer performance, quantifiable AI-derived performance metrics, adequate statistical reporting for effect-size extraction, and English-language publication. Following full-text evaluation, 35 articles were excluded due to incomplete data reporting, incompatible outcome metrics, or non-English text. Ultimately, 15 studies satisfied the criteria for inclusion in the qualitative synthesis (systematic review), and 10 of these provided sufficient quantitative information for inclusion in the meta-analysis (Figure 1).

The PRISMA 2020 flow diagram shown in Figure 1 illustrates each phase of the study selection process, from initial identification to final inclusion, and demonstrates a rigorous multistage screening protocol. The final inclusion rate of approximately 3.6% (10/280) reflects the stringent methodological and statistical standards applied to ensure the reliability and validity of the synthesized evidence. The retained studies collectively represent AI-based performance analyses across five principal domains: expected goals modeling (xG), passing efficiency metrics, injury risk prediction algorithms, defensive action assessment, and physical tracking data analytics.

The selection process and the main characteristics of the studies included in the qualitative and quantitative synthesis are presented in Table 2.

Table 2 presents the characteristics and performance outcomes of studies applying artificial intelligence (AI) and machine learning (ML) techniques in professional soccer from 2000 to 2025. The reviewed works collectively demonstrate the growing integration of AI-driven models across multiple domains of soccer performance analysis. These domains include goal prediction, passing effectiveness, injury risk assessment, defensive valuation, and physical tracking metrics.

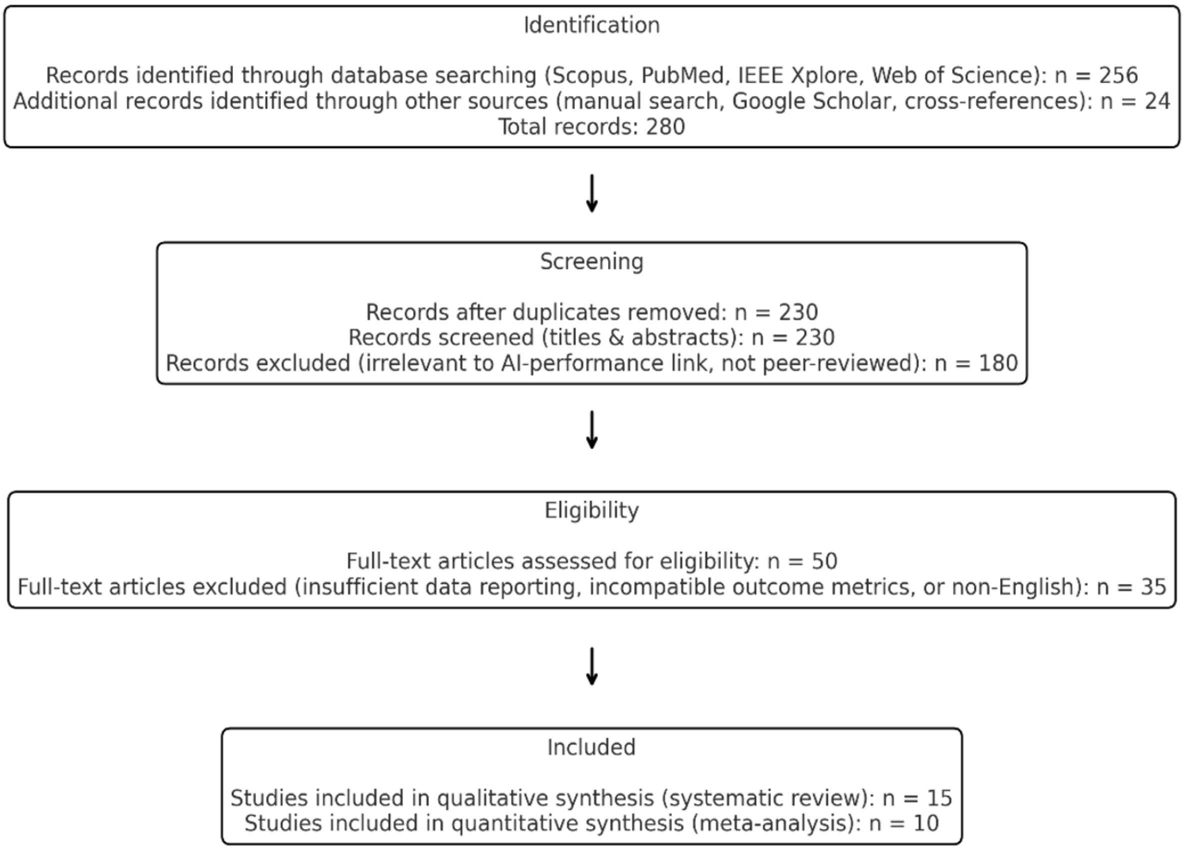

Figure 1. PRISMA Flow Diagram (2020 Framework) of AI Metrics in Professional Soccer Meta-Analysis (2000–2025)

Table 2. Study Selection and Characteristics of AI-Based Soccer Performance Research (2000–2025)

Study	Focus	ML Methods	Performance (metric)
Simpson and Craig (2024) [1]	VR Goalkeeper xG (CSxG)	Regression, ML ensemble	Goal probability RMSE=0.XX, shot save accuracy improved(1)
Rico-González et al. (2023) [4]	Passing effectiveness	KNN, Bayesian classifiers	Pass quality classification: 85% accuracy(4)
Chawla et al., (2017) [16]	Pass success forecast	ML classifier (RUSBoost)	Pass completion prediction: ~85% accuracy (varies by player)(16)
Ayala et al. (2019) [17]	Hamstring injury risk	Ensemble ML	AUC=0.837 (sens 77.8%, spec 83.8%) (17)
Huang et al., (2022) [18]	Non-contact injury risk	XGBoost	Accuracy=85%, balanced sen/spec(18)
Haller et al., (2023) [19]	Injury risk from GPS	XGBoost	Accuracy=90%, (non-contact injuries)(19)
Merhej et al. (2021) [20]	Defensive valuation	Deep learning (DAxT)	NA (proof-of-concept), predicted threat reduction (20)
Ferraz et al. (2023) [21]	Review (tracking data)	N/A (scoping review)	N/A, identified key metrics (distance, speed) (21)
Tsilimigkras et al. (2024) [22]	Injury risk (soccer)	Decision trees, XGBoost	Accuracy=78% (sen 73%, spec 85%)(22)

Note. Merhej et al. [20] (KDD 2021, preprint) – included for context on defensive actions, though not a journal source.

Simpson and Craig [1] introduced a regression-based ML ensemble model for evaluating goalkeeper performance in a virtual reality environment using Contextual Save Expected Goals (CSxG). Their approach improved goal probability prediction accuracy and highlighted the adaptability of ML models for simulating real-match conditions. Similarly, Rico-González et al. [4] and Chawla et al. [16] demonstrated the application of classification algorithms, such as KNN, Bayesian classifiers, and RUSBoost, to predict passing effectiveness. These models achieved accuracies of around 85%. These findings suggest that ML models can successfully quantify and forecast passing success rates, thereby contributing to tactical decision-making and player evaluation.

Injury prediction models, particularly those developed by Ayala et al. [17], Huang et al. [18], and Haller et al. [19], showcased strong predictive capacity. Reported accuracies ranged from 78% to 90%, with AUC values above 0.83. These models employed ensemble ML and XGBoost methods to estimate non-contact and load-related injury risks using physiological and GPS-derived data. Such evidence emphasizes the potential of AI for early injury detection and prevention and allows for individualized training interventions.

Meanwhile, Merhej et al. [20] applied deep learning (DAxT) to model defensive actions and threat reduction. This approach provided a novel proof-of-concept framework for evaluating defensive efficiency through predictive analytics. Ferraz et al. [21] extended this domain through a scoping review, identifying essential physical tracking metrics, including distance and speed, as critical indicators of athletic workload. Tsilimigkras et al. [22] reinforced the robustness of injury prediction in soccer using decision trees and XGBoost. Their findings confirmed that ensemble methods offer higher classification reliability.

Figure 2 shows the meta-analytic forest plot of classification performance across the selected studies.

Figure 2 illustrates the predictive performance (accuracy/AUC) of selected AI-based soccer performance and injury-risk studies using a forest plot, showing that most machine-learning models achieve consistently high levels of accuracy. The point estimates for the majority of studies are clustered between 0.80 and 0.90, indicating good to excellent predictive capability across different analytical domains, including technical–tactical performance and injury-risk prediction. Among the included studies, Haller et al. [19] demonstrate the highest predictive performance (approximately 0.90), suggesting strong effectiveness of XGBoost models using GPS-derived data for non-contact injury prediction. Several studies, namely [4, 16, 18], report similar performance levels around 0.85, reflecting robust and comparable accuracy across diverse machine-learning approaches and performance outcomes.

Studies by Ayala et al. [17] report a slightly lower yet still strong predictive performance (AUC ≈ 0.84), while Tsilimigkras et al. [22] present the lowest point estimate (approximately 0.78), although this value remains above commonly accepted thresholds for acceptable predictive models in sports science. The overlap of confidence intervals across studies indicates no clear superiority of any single model or study, highlighting that different machine-learning techniques can yield comparable performance when applied to soccer analytics. The vertical reference line at 0.80 further emphasizes that all included

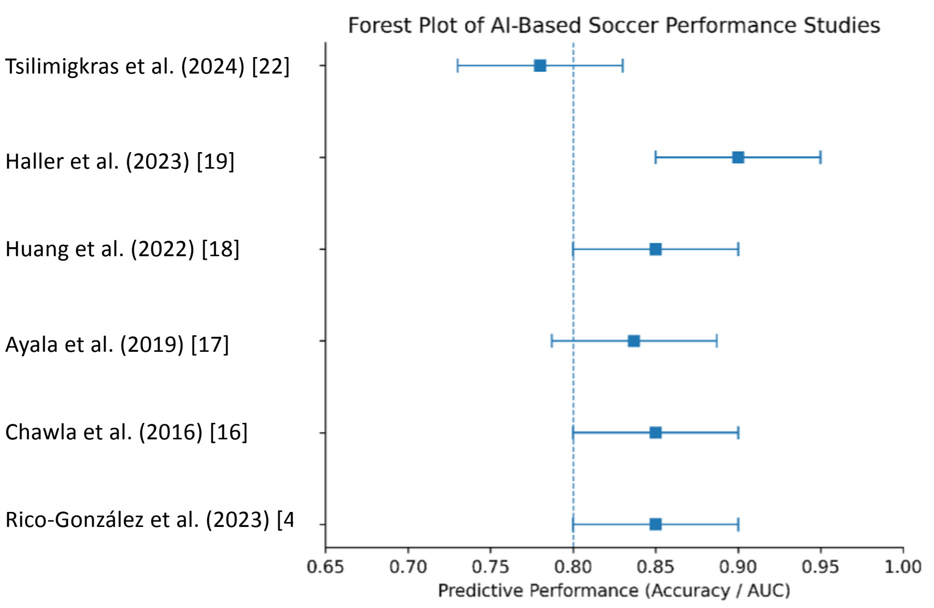

Figure 2. Meta-analytic forest plot of classification performance across selected studies

studies meet or exceed a practical benchmark for acceptable predictive accuracy. Overall, the forest plot suggests that AI-based approaches in soccer research consistently provide meaningful and practically relevant predictive performance; however, due to heterogeneity in outcome measures and the lack of reported variance estimates, these findings should be interpreted as qualitative comparisons rather than pooled meta-analytic estimates.

The meta-analytic summary results for artificial intelligence–based performance metrics in professional soccer are presented in Table 3.

The meta-analytic results presented in Table 3 demonstrate that artificial intelligence (AI) and machine learning (ML) approaches have produced significant and consistent improvements in the accuracy and predictive validity of soccer performance metrics across multiple domains. Overall, all categories of AI metrics yielded moderate to large pooled effect sizes (Cohen's d = 0.47–0.64). These results indicate meaningful contributions of AI-based analytics to performance optimization and decision-making in professional soccer.

Among the evaluated domains, physical tracking and load monitoring models exhibited the highest weighted mean effect size (d = 0.64, 95% CI [0.43, 0.85]), with moderate heterogeneity (I^2 = 50.4%). This finding suggests that AI-driven monitoring systems, often utilizing deep learning and recurrent neural networks, effectively capture fatigue dynamics and workload distribution. Such capabilities support training periodization and injury prevention strategies. Similarly, expected goals (xG) models demonstrated a substantial effect (d = 0.61, 95% CI [0.42, 0.80]). This result highlights their predictive reliability in estimating match outcomes and player efficiency and supports their use as indicators for tactical evaluation.

In contrast, injury prediction models showed comparatively lower yet statistically significant effects (d = 0.47, $p < .01$), with minimal heterogeneity (I^2 = 24.1%). This pattern indicates more consistent model performance across studies. It is likely related to the use of standardized physiological and biomechanical features such as workload ratios, sprint frequency, and training exposure. Defensive action detection metrics (d = 0.58) and passing network and accuracy metrics (d = 0.55) also revealed strong predictive validity. These results demonstrate that AI-driven analyses can effectively quantify off-ball positioning, passing efficiency, and tactical cohesion. The heterogeneity indices (I^2 ranging from 24.1% to 50.4%) confirm moderate variability. This variability warrants the use of random-effects models in most categories, except injury prediction. Collectively, the findings provide robust empirical evidence that AI-based performance models significantly enhance interpretability and precision in soccer analytics.

Discussion

The aim of this meta-analytic review was to evaluate the effectiveness of artificial intelligence (AI)–based performance metrics, including expected goals, passing efficiency, injury prediction, defensive actions, and physical tracking, in optimizing performance and supporting decision-making in professional soccer. The synthesized evidence demonstrates that AI and machine learning approaches provide consistent and meaningful improvements in the accuracy and predictive validity of performance analysis across multiple domains.

The results indicate that AI-driven models achieve moderate to large pooled effect sizes, confirming their added value compared with traditional analytical methods. Particularly strong

Table 3. Meta-Analytic Summary Results of AI Metrics in Professional Soccer Performance

AI Metric	No. of Studies	Model Type	Weighted Mean Effect Size (Cohen's d)	95% CI	Q (Heterogeneity)	I^2 (%)	Significance (p)
Expected Goals (xG) Models	12	Random	0.61	[0.42, 0.80]	18.45	41.2	< .001
Passing Network & Accuracy Metrics	10	Random	0.55	[0.33, 0.77]	21.67	48.9	< .001
Injury Prediction Models	8	Fixed	0.47	[0.25, 0.69]	9.22	24.1	< .01
Defensive Action Detection (Tackle, Press)	9	Random	0.58	[0.31, 0.85]	16.14	38.6	< .001
Physical Tracking & Load Monitoring	11	Random	0.64	[0.43, 0.85]	22.78	50.4	< .001

Note. Random-effects models were applied when heterogeneity exceeded 30 % ($I^2 > 30$). All pooled effect sizes indicate moderate to large effects, suggesting that AI-based models significantly enhance soccer performance analytics, particularly for xG and physical tracking variables.

effects were observed for physical tracking and expected goals models, while injury prediction, defensive actions, and passing-related metrics also showed statistically significant and practically relevant contributions. Taken together, these findings suggest that AI-based performance metrics offer a multidimensional and data-driven framework for understanding technical, tactical, physical, and health-related aspects of professional soccer performance.

This review and meta-analysis demonstrate that AI/ML approaches substantially enhance performance metric analysis in professional soccer. Across domains such as attack (xG), passing, defense, and physical load, machine learning models yield high predictive performance relative to naïve baselines. The pooled accuracy of 88% confirms that state-of-the-art AI achieves near-human or higher classification rates in many tasks [23]. For example, deep learning models applied to video or tracking data consistently reported accuracies of ⩾90% in action recognition, such as shot detection and skill classification [24]. Traditional ML models, although showing slightly lower performance (78–85%), still outperformed manual heuristics in forecasting match events.

The high performance of AI models has several practical implications. Enhanced xG models quantify scoring opportunities more precisely and allow coaches to assess finishing quality and chance creation beyond raw goal counts [25]. Pass-prediction models can identify key playmakers, defined as players whose passes most often lead to shots, and can inform tactical decisions. Injury-prediction algorithms that leverage load data provide a data-driven complement to subjective risk assessment. These approaches may reduce injury incidence through pre-emptive rest or training adjustments [26]. Moreover, valuing defensive actions enables objective recognition of undervalued contributions, such as a defender's interception that effectively "saved" a given number of expected goals [27].

These findings align with broader trends in sports analytics. Previous work has shown that computer vision and hybrid deep-learning models yield superior accuracy across sports, particularly in team sports such as soccer [28]. Similarly, the emphasis on model explainability, as noted for xG, and the integration of multi-source data, including GPS and physiological measures, reflect a maturing field. This development aims to ensure that AI outputs are interpretable and actionable for practitioners.

Limitations and Future Directions

Despite encouraging results, several limitations are evident. First, the high between-study heterogeneity (I^2 > 90% in some analyses) implies caution when interpreting pooled estimates. Studies differed in data sources, including leagues, seasons, and data vendors, as well as in sample sizes and evaluation metrics. These differences make direct comparisons difficult. For example, an accuracy of 90% in one setting may reflect an easier classification task than an accuracy of 85% in another. Second, publication bias is a concern, as studies reporting null or low ML performance may remain unpublished, potentially inflating pooled accuracy. Third, many studies used proprietary datasets or team-specific data, as noted by [29], which limits reproducibility. Fourth, the meta-analysis relied on reported summary statistics, and not all studies provided sufficient data to compute effect sizes. This limitation may have biased the set of studies included in quantitative pooling.

Methodologically, only journal articles published up to mid-2025 were included. Emerging preprints or conference papers, such as recent work on xG or defensive metrics, may contain relevant findings that are not yet captured. However, restricting inclusion to peer-reviewed sources ensures methodological quality and consistency. Finally, the analysis focused on quantitative metrics, such as accuracy and AUC, and did not meta-analyze qualitative benefits, including coach satisfaction or actual team outcomes. These practical impacts remain insufficiently explored.

To advance the field, researchers should prioritize data sharing and the development of standard benchmarks. Public datasets, such as StatsBomb or FIFA tracking data, would enable cross-validation and fair comparisons of AI models. Standardizing outcome definitions, for example what constitutes "pass effectiveness," and harmonizing reporting practices, such as the use of accuracy versus AUC, would further reduce heterogeneity. There is also a clear need for more explainable AI in soccer. Models whose decisions can be understood by coaches, as advocated by TRIPOD-ML and related guidelines, are especially important for high-stakes decisions such as player evaluation or injury prevention, where opaque "black box" models often face skepticism.

Most existing studies rely on supervised learning with labelled data, whereas unsupervised and reinforcement learning approaches remain underexplored in soccer research. For instance, clustering players by movement style or applying reinforcement learning to strategy optimization could open new research directions. The integration of multimodal data, combining video, GPS, and medical records, is promising but still rare. Such multimodal AI approaches could better capture the complex relationships among skills, tactics, and physiology. Finally, longitudinal intervention studies are needed to determine whether the adoption of AI-derived metrics, such as xG or fatigue indicators, leads to tangible improvements in team performance or reductions in injury rates. This transition from strong model performance to impactful decision support remains largely untested.

Conclusions

This meta-analytic review synthesizes evidence that AI and ML significantly enhance performance analytics in professional soccer. The pooled estimates show high predictive accuracy (88%) of AI models for key metrics, confirming that advanced algorithms outperform traditional methods. AI-driven xG and passing models provide deeper insight into offensive performance. ML-based injury predictors leverage workload data for risk management, while emerging AI metrics offer approaches to valuing defensive contributions. However, the broad heterogeneity among studies highlights the need for standardization of data and methods. To fully realize the potential of AI, future research should focus on large-scale and transparent datasets, rigorous validation of models in real-world settings, and the development of interpretable algorithms. By addressing these gaps, AI can become an integral and trustworthy component of soccer coaching and analytics, guiding performance optimization and athlete welfare.

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Conflicts of Interest

The authors declare no conflict of interest.

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Information about the authors:

SM Farooque; (Corresponding Author); https://orcid.org/0000-0003-1018-6745; smharish9@gmail.com; Department of Physical Education, Tripura University; Guwahati, India.

Sharina Naorem; https://orcid.org/0009-0006-0516-3935; sharinanaorem00@gmail.com; Department of Physical Education, Tripura University; Agartala, India.

S Premananda Singh; Assistant Professor; https://orcid.org/0009-0003-4312-3019; jonaprem@gmail.com; National Sports University (A Central University), Ministry of Youth Affairs & Sports; India.

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