Aligning Artificial Intelligence with Soccer Play Styles: A Decision-Based Framework for Context-Dependent AI Use in Professional Soccer

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The use of artificial intelligence (AI) by professional soccer teams for match preparation and a host of other functions, including player evaluation, recruitment and training, is becoming increasingly common. However, practical constraints prevent teams from giving equal attention to every available AI application. One of the most important constraints is the limited time, staff capacity, and financial resources available for coaches and analysts to interpret and implement AI outputs. Research must therefore move beyond describing individual AI applications and provide a framework for determining which applications are most relevant to particular styles of play. This study therefore develops a narrative conceptual framework that aligns AI-supported analytical functions with the tactical demands of different soccer play styles. Drawing on literature concerning human–AI collaboration, soccer analytics, tactics, and styles of play, the study evaluates a broad set of AI applications across five tactical systems using five criteria: decision relevance, data fit, implementation priority, interpretability, and performance connection. Each proposed match was evaluated according to whether the AI application addressed a central tactical decision, used relevant data, could be implemented under realistic resource constraints, produced outputs that coaches could interpret, and connected to a measurable performance outcome. This is a conceptual framework based on existing literature rather than an empirical study of how individual professional teams currently use AI. The framework recommends spatial-control and passing-network analysis for possession-based teams; pressing-coordination and load-management analysis for high-pressing teams; transition-speed and shot-efficiency analysis for counterattacking teams; long-pass, second-ball, and set-piece analysis for direct-play teams; and crossing-pattern and box-occupation analysis for wide-attacking teams. These recommendations are based on the recurring tactical decisions associated with each style, emphasizing that the value of an AI application depends on how closely it addresses those decisions. Because the framework has not yet been empirically validated with club data or practitioner ratings, the recommendations should be understood as theory-driven propositions rather than confirmed performance prescriptions.

Introduction

Coaches have traditionally relied heavily on direct observation when making tactical, training, and personnel decisions. With the vast amounts of data now being collected by teams and being tracked to help coaches with their in-game decisions as well as with player recruitment, player development, training sessions, and injury prevention, coaches are now faced with the problem of how they can use all of this information in order to make the best possible decisions[1–4]. Several studies have provided in-depth reviews of how AI can be used in the analysis of matches, scouting of potential players, the planning and preparation of teams for matches, and other soccer-related issues. TacticAI illustrates how AI can be applied to a narrowly defined tactical problem. The system analyzes corner-kick situations using player-position and movement data, predicts likely receivers and shot outcomes, and suggests alternative player arrangements[2,3]. This example shows how AI can support a specific coaching decision without attempting to automate an entire match. Broader research identifies additional applications involving tactical structures, collective movement, recruitment, performance analysis, and injury prevention[1,5].

In addition to the factors affecting the use of AI in sport, as mentioned above, the value of AI also depends on the goals of a team and organization. Most strategic choices are not the best in all situations; i.e., they depend on objectives, constraints, and context. Research on strategy processes shows that organizational decisions depend on objectives, internal capabilities, managerial practices, and the surrounding environment[6,7]. Studies on organizational strategy also support the view that strategy making is a highly complex process, which involves many actors, internal and external environments and different stages before a strategic decision is implemented[6]. A central challenge for clubs is prioritization: de-

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ciding which information deserves attention depends partly on the tactical problems the team repeatedly faces. A possession-based team, for example, would receive the most benefit from a spatial analysis of the team as a whole and their passing network, as opposed to a team that presses high up the pitch. However, this type of team would benefit greatly from in-depth analysis of the team's movements and how they can be improved, whilst a team that employs a high-pressing style of play would benefit more from an in-depth analysis of the team's movements in relation to that of the opposing team. In addition, the pressing-oriented team would also benefit from an in-depth analysis of how the team's players can synchronize their movements to put the highest amount of pressure on the opposing team possible, as well as how the team can monitor the fatigue of their own players to avoid injury[8,9].

A team's use of technology can be of great value regardless of the team's style of play, as long as the team interprets and implements the technology effectively[5,10–12]. The framework presented in this paper connects five common styles of play with the key decisions a team makes, the information a team would need to support a decision, and a variety of technologies that a team could use to analyze information to support a decision.

Background Literature

AI is increasingly used in settings where large volumes of information must be processed to support complex decisions. The value of these systems depends on how human decision-makers interpret and apply their outputs within a specific decision context. Computerized support of human problem-solving has been a field of research of great importance since the 1960s, as described by Engelbart[13].

Research indicates that, in general, decision-support systems, or AI models, are utilized to provide predictions, simulations, and recommendations to support decision-making. However, these tools may have limited value unless their outputs can be integrated into the judgment of experienced coaches. Therefore, the use of sports analytics does not aim at automating the decision-making process of coaches, but rather at supporting them in order to support their exploration and gain new insights[11]. Therefore, the output of the sports analytics can be used as a starting point for deliberation and needs to be evaluated within the broader match context[14–17]. As Baer et al.[10] stated, AI systems are treated as support for human judgment rather than as a replacement for human judgment. This view of using technology to support human problem-solving is not new. In the 1960s, the term 'augmentation' was first coined by Engelbart[13]. In that sense, the purpose of using AI in professional soccer is to support coaches in their decision-making and in their exploration of potential solutions for the problems they encounter during matches and in their daily work[18–20].

The present analysis focuses primarily on the informational problems faced by coaches and analysts. During live play, coaches cannot consistently observe the ball, off-ball movement, spacing between lines, and the positions of all players simultaneously. Spatiotemporal and event data can therefore help analysts identify patterns that are difficult to observe consistently during a match. AI-supported systems may then assist coaches by organizing these data into interpretable outputs, such as movement patterns, spacing measures, receiver predictions, or tactical recommendations. However, these outputs still require human interpretation before they can inform training or match preparation[2,3].

Several studies reviewed various aspects of the soccer training and match preparation process in which several different AI applications can be used. Firstly, models for the analysis of match behaviour of teams and of their spatial organization are most common. The findings from these models can be used to evaluate aspects such as positioning, team shape, passing networks, pressing, transitions, and also set pieces. In addition, the use of AI models is also found in recruitment, squad planning, and training session preparation. Load management and injury prediction are also aspects of a team's preparation and workload that can be monitored using several different AI applications. Teixeira et al.[5] reviewed a broad body of research on AI-supported tactical and performance analysis in soccer and found that they can be used for a variety of different purposes and that, from the point of view of a team, several different functions need to be addressed by the different AI applications that are used by the team. Hence, from a team's perspective, the different applications must be matched to the team's goals (see Table 2).

A second set of limitations and concerns would stem from the constraints a team faces in terms of the capacity to process information as well as the availability of the coaching and training staff to implement AI systems during training as well as during match preparation. While there are only so many things that a team can do in order to improve, there are only so many things that a team can focus on as well in an attempt to improve given the current state of the organization. In essence, the main limitation or concern would revolve around deciding which of the current systems or types of data that a team currently uses to inform decision making that the team should focus on in order to reach their full potential.

AI use in soccer also creates practical and ethical risks. Elstak et al.[1], for example, identify concerns involving data security, privacy, bias, usability, transparency, and inappropriate workload recommendations. These concerns matter because a technically advanced system may still be unsuitable if coaches cannot interpret its outputs, if the data are unreliable, or if recommendations create risks for players. For this reason, AI adoption should be evaluated not only by technical capabil-

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ity, but also by interpretability, data quality, and responsible implementation.

AI and AI-Supported Analytical Functions in Soccer

For the purposes of this paper, the term AI application refers to a documented system that uses machine learning, predictive modeling, simulation, or algorithmic decision support to produce outputs for coaches, analysts, or recruitment staff. The term AI-supported analytical function is used more broadly for tactical analyses that may be supported by AI but may also rely on tracking data, conventional statistics, or deterministic metrics. When an exact AI implementation is not established in the reviewed literature, the paper treats the item as a proposed AI-supported system rather than a validated AI tool.

The reviewed literature for this paper has identified match-related AI applications in soccer that track and analyze the behaviour of teams and players during matches. Such information can be retrieved by analyzing various aspects of a match, such as tracking of player positions, team shapes, passing networks, pressing behaviours, transitions and set pieces. In addition to match-related applications, AI is also used in non-match situations. Recruitment, squad planning and development, training planning and implementation, monitoring of player workloads as well as the prediction of injury risk are some of the applications that have been reviewed for their use in the domain of soccer [1,5,11].

The range of models that can be used to analyze soccer differs in many ways, the most notable being the type of decision that the model supports and the input and output of the model. For example, TacticAI uses a set of corner kicks where the positions of the players at the moment the ball is kicked are tracked over time to make predictions for likely recipients of crosses as well as to provide a set of suggested reconfigurations of the team to try at future corners. Such models are used to support decisions regarding set pieces. Other models that are used to analyze and support similar decisions include pitch-control models and tracking models. These models take in the locations of players on the field, as well as their speeds and directions of travel over time, and output measures of territorial control, team shape, and defensive compactness. Other models that are used to support decisions of a similar nature to those supported by the previously-mentioned models include opponent-analysis models. These models search for patterns in the behaviour of opponents, such as their typical formations, passing patterns, pressing behaviour, and defensive weaknesses. Finally, there are transition models, which model out the first few seconds of a transition from defence to offence after a possession change-over [12].

Other applications of AI are used for a team's personnel management and physical management. There are recruitment models that support a team's personnel policy by selecting the best players for the team. This can be based on several different criteria such as past performance, the player's age, the player's role on the field, as well as the player's market value. Next, some models support a team's physical management by predicting the likelihood of a player getting injured. These models can be based on many different variables such as the player's sprint speed, the player's acceleration, the player's fatigue levels, as well as the player's current and past workload. Using these models, a coach or trainer can create practice regimens that are designed to avoid putting a player at risk of injury [1,4]. Lastly, there are partnership models that can aid a team's physical management by supporting a coach's partnership choices. These models can measure the chemistry between different player pairs as well as the degree to which different players complement each other in terms of skills [11,21].

These applications and analytical functions may be useful in particular situations, but their value depends on how they support a team's tactical decisions. Existing research provides substantial detail about individual AI applications, including tactical modeling, player tracking, recruitment, injury prediction, and set-piece analysis. However, these applications are usually examined separately rather than in relation to a team's tactical identity. The literature therefore explains what AI can do in soccer more clearly than it explains how teams should prioritize different applications. This gap provides the basis for connecting AI use cases to the recurring decision problems associated with different play styles.

Tactical Dimensions as Decision Contexts

This paper treats play styles as overlapping tactical dimensions rather than fixed categories. Four dimensions mainly describe attacking progression and chance creation: possession-based play, counterattacking, direct play, and wide attack. High pressing is included as a defensive and transition-oriented dimension because it creates a distinct set of AI-relevant decisions involving pressing triggers, compactness, synchronization, opponent build-up, and physical load. Teams may score highly on several dimensions at once; for example, a team may be both possession-oriented and high-pressing. The framework therefore does not permanently classify clubs into one style. Instead, it evaluates how well particular AI-supported analytical functions fit the recurring tactical decisions associated with each dimension.

The five dimensions provide coverage of the tactical contexts most relevant to the framework because each creates a different decision problem for coaches and analysts. Possession-based play concerns spacing, passing lanes, and controlled progression. High pressing concerns when and how a team applies coordinated pressure. Counterattacking con-

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cerns recovery location, first-pass selection, transition speed, and shot quality. Direct play concerns long passes, aerial contests, second-ball recovery, and territory gained. Wide attacking concerns crossing opportunities, delivery type, overloads, and box occupation."

Table 1 summarizes the main bodies of literature used to construct the framework and explains the role each group plays in the analysis.

Methodology

The central research question is: How should different soccer play styles shape the ways teams prioritize and use AI to improve performance? To answer this question, the review develops a conceptual framework connecting soccer AI applications with the recurring tactical decisions associated with five styles of play. It does not attempt to document how individual professional teams currently use proprietary analytics systems, because detailed information about these systems is rarely publicly available. This study is therefore designed as a narrative conceptual review rather than a systematic review. Sources were selected because they contributed to one of three elements needed to construct the framework: human–AI decision support, AI or analytics applications in soccer, and tactical play-style classification. Peer-reviewed studies were prioritized when supporting theoretical or methodological claims. Practitioner and web-based sources were used only to describe contemporary soccer practice, tactical examples, or current playing-style classifications, not to establish the theoretical basis of the framework. The review draws on three groups of literature. Research on human–AI collaboration provides the theoretical basis for treating AI as decision support[10,11,13,19]. Research on soccer analytics identifies the applications available to teams[1,3,5,12]. Literature on play styles identifies the recurring objectives and decision problems associated with possession-based, high-pressing, counterattacking, direct-play, and wide-attacking systems[9,24,25].

Sources were included when they directly informed at least one part of the framework: an AI-supported analytical function, a tactical decision problem, a matching criterion, or an implementation limitation. Sources were excluded when they discussed AI or soccer only generally without contributing to the decision-based framework. This selection process was intended to build a theory-driven framework rather than to estimate the overall effect of AI use on soccer performance.

To organize the analysis, the reviewed AI applications were grouped according to the decisions they support. Applications serving similar functions were combined into broader categories, including tactical decision-making, tracking, spatial control, passing analysis, pressing coordination, transition analysis, recruitment, player partnerships, load management, and set pieces. Table 2 summarizes each category by its purpose, required data, typical outputs, supporting sources, and status as either a documented AI/ML system, an AI-supported analytical function, or a proposed AI-supported system.

These categories can be used to analyze tactical tendencies without permanently assigning a team to one fixed style. Most teams combine elements of several systems. A possession-oriented team that occasionally launches rapid counterattacks would still be treated as possession-based if controlled possession remains its primary tactical approach. Similarly, a team that defends in a low block and attacks primarily through rapid transitions after regaining possession would be treated as counterattacking for the purposes of this framework. Low-block defending is therefore not included as a separate attacking category. Table 3 identifies the main objectives, recurring decision problems, relevant data, and tactical indicators associated with the five play styles.

The matching process was structured in four steps. First, the main tactical objective of each play style was identified using Table 3. Second, each objective was translated into recurring decisions that a team must make, such as when to press, how compact to remain, or how quickly to transition after regaining possession. Third, each decision was connected to the data needed to evaluate it, including player positions, passing sequences, pressing intensity, transition speed, workload, aerial duels, and crossing locations. Finally, these data requirements were compared with the outputs produced by the AI applications listed in Table 2. Together, Tables 2 and 3 connect AI capabilities with tactical data requirements, while Table 4 provides the criteria used to evaluate the strength of each proposed match.

Assessment criteria for matching applications of AI with soccer play styles were determined by the following five indicators (Table 4): 1) decision relevance, 2) data fit, 3) implementation priority, 4) interpretability, and 5) performance connection. By the first criterion, decision relevance, the crucial question is whether the decisions that are supported by the AI are crucial for the given soccer play style. By the second criterion, data fit, the question is whether the data that the AI requires for its calculations correspond with the relevant variables for the given tactical problems of a team. Here, focus is put on the question whether a team is able to generate the required data in an adequate quality and regularly. By the third criterion, implementation priority, the question is how a team should proceed if it is not in a position to implement all possible uses of AI. The fourth indicator, interpretability, asks the question whether the coaches and the analysts of a team are in a position to transform the results of the AI into adequate terms for training, for recruitment, for the preparation of single matches as well as for the tactical decisions during a match. The last criterion, performance connection, refers to the question of whether the results of the AI can be related to concrete performance indicators of a team, e.g. to the degree of pro-

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Table 1 Evidence Base Used to Build the Framework

Literature	Main Sources	What the Literature Shows	Role in This Paper	Evidence Type and Limitations
Human-AI augmentation and decision support	Engelbart[13]; Baer et al.[10]; Pavitt et al.[11]	AI should be understood as a tool that extends human decision-making rather than fully replacing human judgment.	Provides the theoretical basis for treating AI as a decision-support system for coaches and analysts.	Peer-reviewed theoretical and decision-support research. Provides the theoretical basis for human-AI augmentation, but most sources are not soccer-specific and must be adapted to the context of coaching and analytics.
AI in soccer tactical analysis	Wang et al.[3]; Google DeepMind[2]; Plakias et al.[12]; Teixeira et al.[5]	AI can process spatiotemporal data, identify tactical patterns, predict outcomes, and generate recommendations.	Supports the inventory of AI use cases in soccer, especially tactical decision-making, tracking, and scenario generation.	Peer-reviewed soccer AI research and technical AI case studies. Supports documented AI use in tactical analysis, especially tracking and set-piece analysis, but does not directly rank AI tools by play style.
AI in sports applications and risks	Elstak et al.[1]; Xu & Baghaei[4]	AI is used across athlete evaluation, injury prediction, match analysis, performance optimization, and strategic planning, but it also creates concerns involving bias, privacy, usability, and workload decisions.	Shows that AI adoption requires prioritization and responsible implementation, not simply more technology.	Peer-reviewed sports AI review literature. Identifies broad AI applications and risks in sport, but some findings apply across multiple football codes or sports rather than only professional soccer.
Soccer play-style classification	Fernández-Navarro[9]; Power Soccer USA[22]; ESPN[23]; The Analyst[24]; Stephanatos[25]	Soccer teams can be categorized by recurring tactical patterns such as possession, pressing, counterattacking, direct play, and wide attack.	Provides the tactical categories used to match AI applications to play styles.	Mixed evidence: academic thesis plus practitioner/applied soccer analytics sources. Useful for defining tactical dimensions and current examples, but practitioner sources are not used as theoretical proof and team classifications can change by season, manager, and match context.
Player relationships and tactical fit	Mohandas et al.[21]; Pavitt et al.[11]	AI can support partnership analysis, scouting, and match analysis by helping decision-makers interpret complex soccer data.	Supports the use of AI for passing networks, attacking chemistry, recruitment, and tactical fit.	Peer-reviewed AI/ML and soccer analytics research. Supports partnership and tactical-fit analysis, but the evidence focuses on specific player relationships rather than full team-wide tactical systems.

gression, to the degree of pressing success, to the transition speed, to the degree of controlled possession, to the territory gained and/or to the quality of chances. The five criteria are defined in Table 4. Table 5 explains the High, Medium, and Low rating scale, Table 6 illustrates how the ratings were applied to selected AI–play-style matches, and Table 7 presents

Table 2 Inventory of AI and AI-Supported Analytical Functions in Soccer

AI Use Case	What It Does	Main Data Inputs	Typical Outputs	Supporting Sources	Status
Tactical decision-making AI	Predicts likely tactical outcomes and recommends decisions.	Player positions, ball location, match context, event data	Shot probability, pass options, receiver prediction, positioning suggestions	Wang et al.[3]; Google DeepMind[2]	Documented AI/ML system
Spatiotemporal tracking AI	Tracks player and ball movement over time.	Player coordinates, speed, direction, ball movement	Team shape, movement patterns, spacing, compactness	Teixeira et al.[5]; Plakias et al.[12]	AI-supported analytical function
Spatial-control / pitch-control AI	Measures which team controls key spaces on the pitch.	Player positions, velocity, passing lanes, field zones	Pitch-control maps, space occupation, territorial dominance	Teixeira et al.[5]; Dang[8]	AI-supported analytical function
Passing-network AI	Analyzes how players connect through passes.	Pass frequency, pass direction, player location, sequence length	Central players, weak links, progression routes	Teixeira et al.[5]; Mohandas et al.[21]	AI-supported analytical function
Pressing and defensive-coordination AI	Evaluates pressing timing and team compactness.	Defensive actions, opponent build-up, player distances, recovery zones	Pressing triggers, pressure effectiveness, compactness measures	Plakias et al.[12]; Teixeira et al.[5]	Proposed AI-supported system
Transition/ counterattack AI	Analyzes how quickly and effectively teams attack after winning the ball.	Recovery location, first pass, transition speed, defenders behind the ball	Transition efficiency, xG from transitions, direct-attack quality	Plakias et al.[12]; Fernández-Navarro[9]	Proposed AI-supported system
Opponent-analysis AI	Identifies opponent tendencies and weaknesses.	Opponent formations, passing patterns, pressing habits, defensive structure	Scouting reports, tactical vulnerabilities, match-plan suggestions	Pavitt et al.[11]; Plakias et al.[12]	AI-supported analytical function
Simulation / scenario-generation AI	Tests alternative tactical situations.	Historical match data, player positions, tactical constraints	Alternative strategies, scenario outcomes, tactical recommendations	Google DeepMind[2]; Wang et al.[3]	Documented AI/ML system
Recruitment and squad-building AI	Identifies players who fit tactical and financial needs.	Player-performance data, age, role metrics, market value	Player rankings, tactical-fit scores, undervalued targets	Pavitt et al.[11]; Xu & Baghaei[4]	AI-supported analytical function
Player-role / partnership AI	Evaluates player relationships and role compatibility.	Assist-goal interactions, passing links, player combinations	Partnership strength, attacking chemistry, role similarity	Mohandas et al.[21]	Documented AI/ML system
Load-management / injury-risk AI	Tracks physical stress and injury risk.	Workload, sprint load, acceleration, fatigue indicators	Injury alerts, rest recommendations, training adjustments	Elstak et al.[1]; Xu & Baghaei[4]	AI-supported analytical function
Set-piece AI	Optimizes corners, free kicks, and other dead-ball situations.	Player height, positions, movement, delivery type	Receiver prediction, shot probability, set-piece routines	Wang et al.[3]; Google DeepMind[2]	Documented AI/ML system

the final prioritization framework.

Each match was given a rating for each of the five criteria of decision relevance, data fit, implementation priority, interpretability, and performance connection. The three possible ratings were High, Medium, and Low. High indicated that the application was highly relevant and suitable for the relevant decisions corresponding to a style. Medium indicated that the application was somewhat relevant and suitable for supporting the relevant decisions. Low indicated that the application was not very relevant and/or not very suitable for supporting the

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Table 3 Tactical Decision Dimensions

Tactical Dimension	Phase of Play	Main Tactical Objective	Core Decision Problem	Key Data Needed	Example Tactical Indicators
Possession-based	Attacking possession / build-up	Control space and progress through structured possession.	How can the team maintain spacing, create passing lanes, and turn possession into progression?	Player positions, passing sequences, pitch-control data, sequence length	Passes per sequence, pass completion, field tilt, central progression, positional spacing
High-pressing	Defensive recovery / transition	Regain possession through coordinated pressure.	When should the team press, and how can it remain compact while doing so?	Pressing intensity, player distances, opponent build-up patterns, recovery zones	High turnovers, PPDA, recoveries in the final third, distance between lines, pressure success
Counterattacking	Attacking transition	Exploit opponent imbalance immediately after regaining possession.	How can the team attack quickly without reducing shot quality?	Ball-recovery location, first pass, transition speed, xG per transition	Time from regain to shot, direct speed, xG per counterattack, vertical-pass success
Direct-play	Attacking progression	Gain territory through vertical progression and physical contests.	Where should the team play forward, and how can it win second balls?	Long passes, aerial duels, second-ball zones, territory gain	Long-pass percentage, aerial-duel win rate, second-ball recovery, territory gained
Wide-attack / crossing	Chance creation	Create chances through wide areas, delivery quality, and box occupation.	Which wide situations produce high-quality chances?	Cross location, delivery type, box occupation, aerial matchups	Cross completion, xG from crosses, wide overloads, touches in wide zones, aerial targets

relevant decisions, and therefore would not be a priority for development and/or implementation. Note that these ratings were intended to answer the question of relevance for each application across all styles, not to rate the quality of each application.These ratings identify the relative priority of an AI application within a particular tactical context; they do not evaluate the application's overall technological quality.

Table 5 defines the meaning of the High, Medium, and Low ratings used in the matching process.

For the base version of the framework, the five criteria were treated as equally weighted. Each AI–tactical-dimension match received a score of 2 for High, 1 for Medium, and 0 for Low on each criterion. A match was classified as Priority when it received a total score of 8–10 and received High ratings for both decision relevance and data fit. A match was classified as Supporting when it received a total score of 5–7, or when it scored 8 or higher but did not receive High ratings for both decision relevance and data fit. A match was classified as Lower priority when it received a total score of 0–4 or when both decision relevance and implementation priority were Low. These rules make the conceptual rating process transparent, but they do not establish the framework as an empirically validated measurement instrument.

Table 6 illustrates how the rating system was applied to selected AI–play-style combinations. The examples include priority, supporting, and lower-priority applications and demonstrate how the five criteria lead to the overall classifications. The table is illustrative rather than a complete scoring matrix of every possible combination. The author-rated conceptual matrix for the core AI–tactical-dimension matches used to support the final prioritization framework is provided in Appendix A.

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Table 4 Criteria Used to Match AI Applications to Play Styles

Matching Criterion	Guiding Question	Why It Matters	Example
Decision relevance	Does the AI tool support a decision that is central to the play style?	Prevents the framework from matching tools to styles without a tactical reason.	Pressing teams need AI that helps determine when and where to press.
Data fit	Does the AI tool use data that capture the play style's tactical variables?	Ensures that the system is measuring what matters for the style.	Possession teams need positional, spacing, and passing-sequence data.
Implementation priority	Is the tool worth prioritizing given limited time, resources, and coaching attention?	Recognizes that teams cannot maximize every AI use case at once.	High-pressing teams may value load monitoring more than lower-intensity teams.
Interpretability	Can coaches and analysts translate the output into tactical action?	AI creates value only when people can understand and use the result.	A pressing model should produce usable cues, not only abstract probabilities.
Performance connection	Can the output be linked to a style-specific decision-support indicator or outcome proxy?	Clarifies whether the output can be evaluated against a measurable indicator without claiming that the AI itself causes improved performance.	Transition analysis can be compared with time from recovery to shot or xG from counterattacks.

Framework Recommendations

The framework treats AI applications as tools that may support several tactical systems but assigns them different levels of priority according to the decisions each style emphasizes. Table 7 presents the priority applications for each play style, explains why those tools fit the relevant tactical system, and identifies applications that may receive less attention in that context.

These recommendations identify relative priorities rather than exclusive rules. For example, even though spatial-control and passing-network analysis are high-priority tools for possession-based teams, this does not mean that other teams cannot benefit from those applications. The priority tools identified by the framework should be treated as first candidates for further review, pilot testing, or investment. They should not automatically receive the majority of a team's resources. Final allocation should also depend on cost, data availability, reliability, staffing, privacy concerns, and practitioner judgment.

Table 5 Rating Scale for AI–Play-Style Matches

Rating	Meaning
High	Directly supports a central tactical decision and shows strong data, implementation, interpretability, and performance alignment.
Medium	Provides useful support but is not essential to the play style, or requires additional interpretation before use.
Low	Has limited tactical relevance, weak data alignment, or low implementation value for the play style.

After tactical priority is identified, each proposed application should pass a second-stage feasibility assessment. This assessment considers cost, data availability, data reliability, staff expertise, privacy risk, and ease of integration into training or match preparation. This second stage prevents the framework from implying that a tactically relevant application should automatically be adopted regardless of organizational constraints.

Possession-Based Teams

For possession-based teams, spatial-control AI should be the application of greatest focus for the coach and analyst, in order to improve Spatial Control, Passing Structure and the Team's Build-up. The team is not simply trying to maintain long periods of possession and therefore spatial control of pitch space or territory is critical. The spatial organization of the team during possession can be contrasted with that during pressing in order to reveal key differences and for the coach and analyst to understand the team's overall organization on the pitch. Using a spatial organization model during the match, for example, the coach and analyst can assess whether the team is currently utilizing possession effectively to gain pitch space or territory.

By implementing a spatial-control AI model, the possession-based team can check whether their possession of the ball translates into space on the field and thereby

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Table 6 Illustrative Application of the AI–Play-Style Rating System

Play Style	AI Application	Decision Relevance	Data Fit	Implementation Priority	Interpretability	Performance Connection	Overall Classification
Possession-based	Spatial-control analysis	High	High	High	High	High	Priority
Possession-based	Crossing-pattern analysis	Medium	Medium	Low	High	Medium	Supporting
High-pressing	Load-management analysis	High	High	High	High	High	Priority
High-pressing	Long-pass analysis	Low	Medium	Low	Medium	Low	Lower priority
Counterattacking	Transition-analysis model	High	High	High	High	High	Priority
Direct-play	Second-ball recovery analysis	High	High	High	Medium	High	Priority
Wide-attacking	Box-occupation analysis	High	High	High	High	High	Priority

puts pressure on the opponent. The team can keep possession for a long time, but still be very contained and have their players operating in narrow bands, lacking flexibility. Using a pitch-control analysis model and/or tracking data allows the coach to check who is available to receive the ball in order to influence the team's spatial organization. The coach can also check where on the field his players are positioned in order to overload opponents in certain areas of the field and then progress with the ball after making a pass. The coach can then use a passing-network model to check for central players, weak points in the team's passing, common patterns of play, and overconcentration by the team in certain areas of the field. All this information can then be used by the coach to make decisions regarding the spatial organization of the team in order to create a very effective possession-based team. A partnership model is also very valuable, as the relationship of players in possession of the ball is a crucial factor for the possession-based team. By analyzing data on the relationships of players in possession of the ball, the coach can identify the best roles for the different players on the team in order to create a very successful possession-based team of players. For example, the relationship between a fullback and a winger could create a lot of attacking opportunities, or the relationship between a midfielder and a striker.

Another important tool that can be used by possession-based teams is partnership analysis by AI. These types of teams rely heavily on a set of individual players and the relationships between them in order to maintain possession of the ball and create scoring opportunities. By using machine learning to model these partnerships using data on assist and goal interactions between different players, coaches and

analysts can gain valuable insights into the ways in which their players interact with each other. For example, research has shown that models created by the use of machine learning to model attacking partnerships using data on assist and goal interactions between different players can identify several meaningful partnerships, as well as predict the likelihood that different players may form a partnership with each other in future matches[21].

For example, Manchester City and Arsenal have traditionally operated possession-based structures in recent years[24]. For coaches and analysts working within such structures, the above examples of spatial and relational data can be particularly useful for gaining insight into how the team as a whole moves collectively and how individual players contribute to the team's overall structure to facilitate effective possession of the ball and progress through compact defensive formations. The body of literature that focuses on formations has already highlighted the use of spatial and relational data in order to gain insight into teams' collective movement[5].

High-Pressing Teams

High-pressing teams can constantly move up and down the pitch in search of winning the ball back as quickly as possible. For this type of team to be effective, however, all the lines (defenders, midfielders, and forwards) must move as a coordinated unit. The pressure from the front line of players must be supported by all other players, and the team must remain compact. AI analysis for high-pressing teams should focus

Table 7 AI–Play-Style Prioritization Framework

Play Style	Priority AI Applications	Why These AI Tools Fit	Lower-Priority AI Focus
Possession-based	Spatial-control analysis; passing-network analysis; build-up simulation; player-partnership model	Possession teams depend on spacing, passing lanes, positional structure, and repeated player relationships.	Pure transition-speed AI is less central unless the team also uses frequent counters.
High-pressing	Pressing-trigger analysis; movement-synchronization model; opponent build-up analysis; load-management analysis	Pressing depends on timing, compactness, coordinated movement, and physical sustainability.	Long-ball and crossing AI may be less central unless the team also attacks directly.
Counterattacking	Transition-analysis model; opponent-imbalance detection; shot-efficiency model; player-role model	Counterattacking depends on quick first passes, vertical runs, and exploiting space before defences reset.	Slow build-up simulation is less central than transition timing and chance quality.
Direct-play	Long-pass analysis; second-ball recovery analysis; aerial-matchup analysis; territory-gain analysis; set-piece analysis	Direct play relies on vertical progression, physical matchups, second balls, and dead-ball opportunities.	Short-passing-network AI is less central unless the team also uses controlled build-up.
Wide-attack / crossing	Crossing-pattern analysis; spatial-overload analysis; box-occupation analysis; aerial-matchup analysis; set-piece analysis	Wide attack relies on delivery quality, overloads, movement into the box, and aerial targets.	Central passing-network AI may be less central than wide-zone and box-occupation analysis.

on five areas: pressing triggers, movement synchronization, defensive compactness, opponent build-up, and physical-load monitoring.

First, a model to identify press triggers can be created to identify moments in which the team can press, such as an opponent who loses his first touch in a bad spot, playing a backward pass, a slow cross to the outside of the field, or the goalkeeper receiving the ball under pressure. Then, the team's movement can be tracked to see if other players are following up to press, and the distance between lines, height of the defensive line, number of passing options near where the ball is regaining, and so on. This analysis can show whether the team applies pressure as a coordinated unit or whether individual players press in isolation.

Also for high pressing teams, analyzing how a team and players can sustain their physical efforts over long periods of time is important. The recommendations derived from analyzing pressing triggers are only good if a team can implement these in practice. By using load management and injury risk models, a coach can monitor the movements of his team and players as well as their physiological profiles during training and between matches. This enables the coach to do the best possible with his players during training as well as between matches [1,4,8].

AI supporting a high press should serve two purposes: improving the timing and coordination of pressure and monitoring physical load so that the press can be sustained. Liverpool, for example, have displayed both possession-based and high-pressing tendencies during recent tactical periods, showing why the framework treats styles as overlapping dimensions rather than fixed categories. Other teams, such as Newcastle United in 2019-20, Bournemouth in 2018-19, may also be pressing in certain seasons or under certain managers. The key point is that pressing is a core component of their wider tactics and analysis of this sort must account for how the team recovers the ball and how the opposing team builds from the back in order to create effective pressing moments. Long-ball and crossing analysis will from time to time reveal quick counterattacking opportunities (as in the case of Bournemouth in 2018-19), but such analysis would be of a lower priority to that which supports the key elements of a team's own press and their opponents' build-up from the back, as well as their own and opponents' physical loads.

Counterattacking Teams

At its core, all of a team's play is determined by the decisions made following the team's recovery of the ball and subsequent

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use of that possession. For a team employing a counterattacking style of play, these decisions will typically revolve around the location in which the ball was regained, the direction of the team's first pass, and the speed at which the team's forward players make runs to create as many high-quality scoring opportunities as possible, all prior to the opponent regrouping to return to their organized team shape. Therefore, in addition to the spatiotemporal models that analyze player and team movement throughout the entire match, a coach could also look to implement the use of transition analysis, opponent-imbalance detection, shot-efficiency prediction models, opponent analysis, and player-role profiling to implement AI into their coaching to gain a competitive advantage.

The transition-analysis model can help to provide coaches and other analysts with a range of statistics regarding a team's transitional movement. The system is able to track the time of the shot from the moment that a team recovers the ball until the shot is taken, allowing for an evaluation of a team's ability to transition from defence to attack quickly. The system is also able to provide a range of other statistics that are relevant to transitional movement, including the number of opposing defenders positioned between the ball and the goal when possession is regained. These statistics can be used by coaches and other analysts to better understand a team's transitional movement and to identify situations in which the team's fast transitional movement leads to high-quality shots on goal. In this sense, the transition-analysis model can be used to provide a measure of a team's ability to complete transitional passes and to implement direct attacks effectively.

The evaluation of performance for teams employing a counter-attacking style of play can be challenging given that these teams are likely to complete fewer attacks than their possession-oriented counterparts. However, when assessing the performance of a team employing this style, the focus should not be placed on raw numbers of completed attacks. Instead, various metrics including average expected goals per transition, average time from a team regaining possession until creating a shot, percentage of vertical passes completed, and direct-attack efficiency provide a more adequate evaluation of a team's overall performance. As previously noted, the use of player-role models can also be of value in identifying specific players well-suited for a counter-attacking style of play. For example, fast runners, vertical passers, ball carriers, and forwards capable of scoring within a short amount of time after having regained possession are examples of players that a coach using AI to inform his/her analysis of a team may identify. Much research has been conducted utilizing AI for tasks such as scouting and the collection of and subsequent use of match-analysis information[11]. There is also significant research focusing on the AI-based modelling and analysis of relationships between players[21].

Club examples should be treated as season-specific illustrations rather than permanent classifications. Teams may display counterattacking tendencies under particular managers or match conditions, but the framework focuses on recurring tactical decisions rather than assigning fixed identities to individual clubs. The earlier examples highlighted how AI can be used by coaches and analysts to identify a counterattacking style of play that can be some different things depending on the team and the time period. In the case of the three examples above, the focus would be on the initial seconds of gaining possession and how the team can turn this into quality opportunities, fast.

Direct-Play Teams

Direct-play teams seek to move the ball forward quickly, often through early vertical passes and long balls. The central decisions concern where the first forward pass should be directed, which players should contest the aerial duel, where the second ball is likely to fall, and whether the sequence produces meaningful territorial gain. For this tactical dimension, the most relevant analytical functions include long-pass/direct-progression analysis, second-ball recovery analysis, aerial-duel evaluation, territory-gain analysis, player-role analysis, and set-piece analysis.

For direct-play teams, passing-network analysis must be interpreted differently than it is for possession-based teams. Rather than emphasizing short central combinations, the analysis should focus on long and vertical passes, receiving zones, aerial contests, second-ball recovery, and territory gained. Analyzing the long passes and their targets as well as the vertical passes and their receiving players is central for the analysis of the passing network of teams playing in a direct-play style. The model should display the zones in which a player receives a pass, and the zones in which the support for the first duel is provided and the team recovers the second ball. The AI-supported analysis can then show which types of deliveries lead to territory and to chances, and which types of deliveries only return the ball to the opponent.

For direct-play teams, analysis of set pieces is of higher value. Given the teams' way of playing, they apply a lot of pressure on the opponent using their physicality. This can result in a large number of corners, free kicks, long throw-ins, and other structured situations. These types of situations can be analyzed and compared to others. For example, TacticAI has already developed a model that predicts and generates corner-kick strategies based on the positions and movements of the players[3]. The analysis of set pieces for tactical decision-making is also a growing field of research in soccer, in addition to the analysis of other situations[26].

To distinguish between positive direct-play strategies and long-clearing strategies that do not yield enough returns, a team's AI has to help in identifying, analyzing and distin-

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guishing between good first balls, effective first duels and the team's way of retrieving the second ball and the gains in terms of territory that the team can make. Teams such as Brentford, Everton, or Bournemouth may display direct-play tendencies during particular seasons or under particular managers, although the classification should depend on the tactical period being analyzed.

Crossing and Wide-Attack Teams

Teams that implement a wide-attack style of play aim to create a large number of wide situations in order to provide their attacking players with opportunities to cross the ball into the penalty area. The main problem that these types of teams face is trying to determine which of the wide situations that they create will result in the team producing high-quality chances. In order to be able to make this determination, the team will also need to identify the type of delivery that will be most effective given the specific players in the penalty area for the team. The team will also need to identify how the attacking players can best occupy the scoring zones to be effective. This would make the following AI applications most relevant for a team that sets up in a wide-attack style of play: Crossing-pattern analysis, spatial-overload models, box-occupation analysis, aerial-matchup AI, set-piece analysis, and player-role profiling.

A spatial model for controlling space can help to determine whether a team is creating a numerical or positional overload in wide areas of the field. A subsequent analysis of crossing patterns by zone of play can determine whether the team is crossing the ball from wide areas of the field and the type of delivery that is being created (i.e. crossing the ball into the box and creating an aerial challenge for the opposing team's players or crossing the ball into the box and having the ball cut back quickly to the player who crossed the ball or playing the ball on the floor to players who are making late runs behind the defense). A spatial model for controlling the box can help to identify the number of attacking players that are taking up space inside the penalty area for a team, the spaces that these players are taking up and whether or not these players have a favourable one-on-one situation against the opposing team's players. The player models for roles in wide attacking systems can help to identify whether or not a team has a player who is consistently able to deliver crosses into the penalty area with precision. Additionally, the models can identify whether or not a team has players who are able to make effective overlapping runs down the sides of the field in order to provide width to the team's attacking shape. The models can also identify whether or not a team has tall, physical players who are able to win aerial challenges in the penalty area and whether or not the team has players who are able to arrive in time to receive cut-back passes from wide attackers in order to create scoring opportunities.

Secondly, for wide-attacking teams, crossing-pattern analysis can help to distinguish between crossing volume and value. Whilst passing crosses into the opposition box does not win games, there are many factors which influence the chances created by such crosses, including the location of the box, the defensive set-up, the movement of the attacking players and the resulting shot. The AI can link these factors together to determine which situations are likely to create chances for the team. Crossing-pattern analysis can also be useful when a possession-based team is building up play through the wide areas of the field. Here, the AI can provide insight into the wide-area and box-occupation analysis, and help the team to develop effective strategies for delivering crosses into the opposition's penalty area.

Discussion

AI in soccer analysis has traditionally been examined by looking at current practices and implementation of different applications. By using a framework for AI strategy, a human-AI augmentation strategy can be developed that outlines how different applications can be used to support the coach and analysts of a team to improve their decision-making. More importantly, the framework outlines how the same technology can be of greater value to different teams depending on the problems that they are trying to solve in order to achieve their goals. To this end, the paper develops an AI strategy framework based on the recurring decision problems associated with the five play styles. The recurring decision problems associated with each play style are evaluated using the five criteria to determine the relative value of different AI applications. The result is a framework that can be used to help support coaches and analysts to determine how best to use available technology in order to support their work.

In the end, a technical system can have the very same value for very different teams. While player tracking data is not equal to possession data or pressing data, it can be used to analyze a team's positioning and passing channels, to help a possession-based team and to measure the timing and compactness of a team's pressure as well as the distance between the lines of a team's players, to support a high-pressing team. In addition, tracking data can also be used to analyze transition-based play, including a team's speed of transition and the number of defenders a team leaves behind the ball in order to support a counterattacking team.

Many applications can support several tactical dimensions, but teams still need to establish clear priorities. In this framework, high-priority tools are those that support frequently occurring tactical decisions, rely on relevant data, can be interpreted by coaches and analysts, and connect to measurable decision-support indicators. This does not mean that lower-

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priority tools lack value; rather, they are less directly connected to the tactical problem being evaluated.

While many models and analytical functions are now available, clubs differ in their ability to use them effectively. Budget, staff expertise, data access, privacy constraints, and integration into training all affect whether a tactically relevant application can be implemented. For example, a high-pressing team may benefit conceptually from pressing-coordination and load-management analysis, but only if it has the tracking data and staff capacity needed to interpret those outputs. A possession-oriented team may benefit from transition analysis, but spatial-control and passing-structure analysis are more directly connected to its central tactical problems. The framework therefore helps direct limited analytical attention toward the problems most closely tied to a team's tactical priorities.

For use in soccer analysis, it is important to study the implications the use of AI has on the organization itself. Coaches and analysts must be able to interpret the insights gained from the models, and integrate the insights into their training and match preparation. Studies have investigated the ways in which information changes as it moves through an organization[18]. More recently, there has been considerable research into the complex interactions that occur between experts and AI systems[16,17,20]. Just as the insights provided by the best model are of little use to coaches if they do not understand how the model arrived at its conclusions (and the insights are therefore not interpreted in the correct light), in the same way the best organization with the best technology is of little use to the team if the model is not interpreted correctly by the analysts and coaches.

Similarly, recruitment models need to be evaluated by how well a team can be filled by players of different attributes depending on the team's style of play. For instance, a possession-oriented team will look for a large number of players that can perform well in the heart of the action and are able to receive

the ball in situations where they are under a lot of pressure. They would look for a large number of players who are able to create passing connections and who can play in several different positions while maintaining a solid and disciplined position on the field. On the other hand, a team that uses a lot of counterattacking would look for a smaller group of players that are able to move into space very quickly. They would look for many players that are able to make very long passes down the field in order to find open teammates as the team is moving quickly from the defensive third of the field to the offensive third. These types of players are able to take advantage of spaces that have opened up as the team is moving quickly and are able to provide a number of scoring opportunities for the team.

AI adoption also creates governance and ethical concerns. Elstak et al.[1] discuss risks involving security, usability, bias, and inappropriate load-management recommendations, while Xu and Baghaei[4] identify broader concerns involving privacy, transparency, and algorithmic bias. Teams should therefore assess whether the necessary data are reliable, whether outputs can be scrutinized, and whether recommendations can be implemented responsibly. These concerns support the paper's argument that AI adoption should be treated as a strategic and organizational decision rather than a simple technological upgrade.

Limitations and Future Research

This paper has some limitations. The study is conceptual in nature based on existing studies on soccer tactics and the applications of AI in sports. Given the nature of elite soccer clubs and their proprietary knowledge bases and technology, it is highly unlikely that clubs would reveal details of their individual models, data, and decision-making processes. As a result, this paper does not provide evidence of clubs currently utilizing AI for particular purposes. Rather, it offers a conceptual framework that can be used by clubs in deciding how best to utilize current and future AI technology in line with the team's current tactical identity and subsequently in planning and decision-making.

The framework has not yet been validated by professional coaches, analysts, or club decision-makers. Its recommendations should therefore be understood as theory-driven propositions rather than confirmed practitioner priorities. A next stage of research should ask coaches and analysts to score the AI–tactical-dimension matrix and compare their ratings with the proposed classifications.

The framework was established using a limited set of criteria and tactical dimensions. These dimensions are not intended to describe fixed team identities. Instead, they identify recurring decision problems that may appear together within the same team. Because teams often combine tactical approaches, future research could represent teams using continuous scores across several dimensions rather than assigning them to one primary category. There is also scope for alternative weights to be assigned to the criteria, or for additional criteria such as cost, data reliability, privacy risk, and staff expertise to be included in the assessment process.

This paper does not conduct a full sensitivity analysis of alternative criterion weights. Future research should test whether the final priorities remain stable when different weights are assigned to decision relevance, implementation priority, interpretability, and performance connection. This would help determine whether the framework's recommendations are robust or dependent on the weighting assumptions used in the base model.

It must be noted, however, that teams are not one-dimensional and so play in different ways in different matches. A team that is a high-press team for most of the match can be-

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come a deep defensive team to protect a lead in the latter stages of the match. Similarly, a direct approach team can become a possession-based team to score a goal quickly when losing a match. Injuries to key players can cause a team to play in a different style, and the competition schedule can cause a team to play in different ways in different matches. The manager of the team is also an important factor in a team's style of play, and so a team can play in a different style when a new manager takes over the team. Therefore, it is more accurate to rate teams using the different styles of play as the criteria, rather than rating them within a classification of one style of play.

Several different studies are currently required to test the assumption that using a number of different tools increases a team's performance. These studies could focus on several different areas, including the analysis of match data, studies that compare the analytical practices of different clubs, and in-depth interviews with coaches and analysts who use a variety of different models. The findings from such studies would be of considerable interest in terms of determining whether or not there are any differences in terms of performance increase between those teams whose use of AI is more aligned with their tactical identity than other teams.

In addition to a team's play style, there are several other factors that can affect how a team could prioritize a number of different AI-based applications. Such factors as a team's budget, average age of players, past injuries to players, the team's coach/manager, the team's current position in the league, a team's academy and development system, the team's transfer strategy, and the size of a team's analytics department are all examples. A team with a large budget and a large data department could explore the development of several different models, or utilize a wide array of currently available AI-based systems. A team with limited resources would be able to focus on a few different areas and allocate their resources effectively. A team with a young average age of players would be able to utilize workload monitoring and a variety of other development-related tools. In contrast, an older team would benefit from the use of a number of different recovery-related tools in order to ensure that their players are available for matches. This type of research should also attempt to consider a greater range of key variables that affect decisions around technology in soccer, including club budget, average age of the first team, injury record of the first team, the playing style of the first team, the role of the academy, the playing style of reserve and youth teams, style of recruitment, the development remit of analysts, the current style of analysis, amount of information currently available to analysts, number of staff in analyst function, the playing style of opponents the team face regularly. Utilizing case studies of clubs within the Premier League, practitioners currently working within analyst roles within soccer and quantitative analysis of current practice, this future research could be used to test the developed framework, assess the current set of applications for use of technology within soccer and aid in future development.

Conclusion

As AI becomes more common in soccer analysis, coaches and analysts face a growing problem: deciding which available information deserves attention. The value of an application depends not simply on the data it processes, but on whether its outputs address the tactical decisions a team repeatedly faces. Possession-based teams should place greater emphasis on spatial-control, passing-network, partnership, and build-up analysis. High-pressing teams should prioritize pressing coordination, opponent build-up analysis, and workload monitoring. Counterattacking teams should focus on transition speed, opponent imbalance, and shot quality. Direct-play teams should emphasize long-pass effectiveness, aerial contests, second-ball recovery, territory gain, and set pieces. Wide-attacking teams should prioritize crossing patterns, wide overloads, box occupation, and aerial matchups. Different AI-supported analytical functions can create value for different tactical reasons. The framework developed in this paper helps explain why the value of a tool depends on the decision problem it supports rather than on the sophistication of the tool alone. A larger club may be able to explore many systems at once, while a smaller club may gain more practical value by focusing on a narrower group of applications that directly fit its tactical priorities.

However, the utilization of AI and respective tools has to be a strategic issue and not just a question of affordability. With the majority of clubs being restricted in their resources and having a limited capacity to process the ever-increasing volume of information that can be collected, it is not enough that coaches and analysts can work with the insights generated by the various models and methods [1,11]. The respective tools have to be implemented in a way that they are efficiently incorporated into the decision-making process of a team. Therefore, the respective AI output has to be thoroughly understood by the coach or analyst who implements it in the team's decision-making [20]. Thus, having numerous possible tools at a team's disposal does not automatically translate into better performance.

Future research should test whether greater alignment between AI-supported analysis and tactical decision problems is associated with stronger practitioner judgments, better decision quality, or improved team performance. Such research could use practitioner interviews, expert scoring exercises, club case studies, or quantitative match data. Until such validation is conducted, the framework should be read as a conceptual model for strategic prioritization rather than as empirical proof that particular AI applications improve performance.

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Appendix A. Conceptual Rating Matrix for Core AI-Supported Functions

Table A1

AI-supported function	Possession-based	High-pressing	Counterattacking	Direct-play	Wide-attack / crossing
Spatial-control / pitch-control analysis	10 — Priority	7 — Supporting	6 — Supporting	4 — Lower priority	7 — Supporting
Passing-network analysis	9 — Priority	6 — Supporting	4 — Lower priority	6 — Supporting	6 — Supporting
Pressing and defensive-coordination analysis	5 — Supporting	10 — Priority	6 — Supporting	3 — Lower priority	4 — Lower priority
Transition / counterattack analysis	6 — Supporting	6 — Supporting	10 — Priority	7 — Supporting	4 — Lower priority
Load-management / injury-risk analysis	5 — Supporting	10 — Priority	6 — Supporting	6 — Supporting	5 — Supporting
Set-piece analysis	6 — Supporting	5 — Supporting	6 — Supporting	9 — Priority	8 — Priority

Table A1 provides the author-rated conceptual matrix used to support the prioritization framework in Table 7. Rather than serving as an empirically validated scoring instrument, the matrix makes the reasoning behind the framework transparent by showing how major AI-supported analytical functions

were matched to each tactical dimension. Scores are based on the five equally weighted criteria defined in Table 4: decision relevance, data fit, implementation priority, interpretability, and performance connection. Each criterion was rated High = 2, Medium = 1, or Low = 0, producing a total score out of 10. A match was classified as Priority when it received a total score of 8–10 and received High ratings for both decision relevance and data fit. A match was classified as Supporting when it received a total score of 5–7, or when it scored 8 or higher without receiving High ratings for both decision relevance and data fit. A match was classified as Lower priority when it received a total score of 0–4, or when both decision relevance and implementation priority were rated Low. Because the matrix was developed by the author from the reviewed literature rather than independently validated by professional coaches or analysts, the ratings should be interpreted as theory-driven propositions that future research can test or revise. The matrix shows that most AI-supported functions have some value across several tactical dimensions, but the strongest matches occur when the analytical function directly supports the recurring decisions of that dimension. Spatial-control and passing-network analysis receive the highest scores for possession-based play because they address spacing, passing structure, and controlled progression. Pressing and defensive-coordination analysis and load-management analysis receive the highest scores for high-pressing because they support pressing triggers, compactness, synchronization, and physical sustainability. Transition analysis receives the highest score for counterattacking because it directly evaluates recovery location, first-pass speed, attacking transition, and chance quality. Set-piece analysis receives high ratings for direct-play and wide-attack dimensions because those styles often depend on aerial contests, delivery quality, second-ball situations, and structured dead-ball opportunities. This appendix does not validate the framework empirically. Instead, it makes the author's rating procedure transparent so that future researchers, coaches, or analysts can test, revise, or independently score the same AI–tactical-dimension combinations.

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