From Moneyball to AI: The Disruptive Potential of AI in Football Scouting and Performance Analytics

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Abstract

This dissertation investigated how artificial intelligence (AI) potentially disrupts football scouting and performance analytics as well as adoption dynamics shaping implementation. Moneyball is treated as an historical data analytics reference in professional sports. Moneyball disrupted baseball but did not yield comparable transformation in football. AI represents the next step for football disruption.

This study employed a mixed-methods design, combining quantitative data from a consumer survey of 106 respondents with qualitative insights from 12 expert interviews from the football industry on barriers and drivers of AI in football scouting. Regressions and mediator/moderator tests identified determinants of acceptance and perceived disruption, while qualitative content analysis assessed experts' opinions.

The research indicated AI is a complement rather than a substitute for human scouts, with long-term strategic alignment and ownership structures supporting data-driven decision-making. Building internal club capabilities and proprietary models will be a crucial differentiator. Perceived as barrier by literature and experts, the survey suggested latent AI acceptance by fans (56.6% neutral, 25.5% high). This study provides insights into technology adoption and perceptions in a dynamic, emotionally charged, and closed environment.

Keywords: AI, Football Scouting, Moneyball, Performance Analytics, Fan Acceptance, Innovation Diffusion, Dynamic Capabilities

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Resumo

Esta dissertação analisa o potencial disruptivo da inteligência artificial (IA) no scouting e análise de desempenho no futebol, bem como as dinâmicas de adoção que influenciam a implementação. O conceito Moneyball é utilizado como referência histórica de métodos analíticos baseados em dados no desporto profissional. Apesar de ter revolucionado o basebol, Moneyball não gerou transformação equivalente no futebol. A IA surge como o passo seguinte com potencial para provocar disrupção significativa nesta modalidade.

Este estudo utiliza uma abordagem de métodos mistos, combinando dados quantitativos obtidos através de um inquérito a 106 adeptos com dados qualitativos de 12 entrevistas a especialistas da indústria do futebol, focadas nas barreiras e nos fatores impulsionadores da adoção da IA no scouting. Foram realizados testes de regressão e de mediação/moderação para identificar determinantes da aceitação e perceção de disrupção, complementados por uma análise de conteúdo qualitativa que avaliou as perspetivas dos especialistas.

Os resultados evidenciam que IA constitui um complemento, e não um substituto, para o trabalho dos olheiros humanos, sendo que o alinhamento estratégico de longo prazo e as estruturas de propriedade adequadas favorecem a tomada de decisões baseada em dados. O reforço das capacidades internas dos clubes e o desenvolvimento de modelos proprietários surgem como fatores diferenciadores críticos. Embora a literatura e os especialistas identifiquem a aceitação como barreira, o inquérito revelou sinais de aceitação latente por parte dos adeptos (56,6% neutros; 25,5% elevada). Este estudo contribui para compreensão da adoção tecnológica e perceções num contexto dinâmico, emocionalmente carregado e de acesso restrito.

Palavras-chave: Inteligência Artificial, Scouting no Futebol, Moneyball, Analise de Desempenho, Aceitação dos Adeptos, Difusão de Inovação, Capacidades Dinâmicas

Título: Do Moneyball à IA: O Potencial Disruptivo da IA no Scouting e na Análise de Desempenho no Futebol

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Statement on the Use of AI and Digital Tools

This statement is provided to emphasize transparency and academic integrity.

During the course of this dissertation, certain digital tools were used to support the research and writing process. Connected Papers was used to map academic literature and identify relevant research works. ChatGPT was utilized for additional research support, clarifying concepts, and refining language and phrasing in non-substantive sections. Grammarly was used for grammar, spelling, and style checks.

At no point were these tools used to generate original research content, create data, or produce analytical results. All research design, data collection, analysis, interpretation, and conclusions presented in this dissertation are solely the work of the author.

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AI – Artificial Intelligence
DEA – Data Envelopment Analysis
EPV – Expected Possession Value
KPIs – Key Performance Indicators
LLM – Large Language Model
MA – Moneyball Approach
ML – Machine Learning
MLB – Major League Baseball
OBP – On-base Percentage
PEI – Performance Efficiency Index
PL – Premier League
PU – Perceived Usefulness
TAM – Technology Acceptance Model
VAEP – Valuing Actions by Estimating Probabilities
VIF – Variance Inflation Factor
xA – Expected Assists
XAI – Explainable AI
xG – Expected goals
xGI – Expected Goal Involvement
xT – Expected Threat

1 Introduction

Data analytics and big data have evolved significantly over the last two decades, not only in business but also in industries such as professional sports (Gerrard, 2016). The ability to process big data is revolutionizing traditional decision-making processes. In football, performance analytics, scouting, and player evaluation are evolving. The Moneyball Approach (MA) (Michael Lewis, 2003) exposed inefficiencies in player valuations in American Major League Baseball (MLB) and revolutionized data analytics in the sports industry.

Lewis describes how the Oakland Athletics exploited advanced data analytics to make data-driven decision-making that allowed them to compete with wealthier rivals. Billy Beane's staff recognized higher correlation between metrics such as on-base percentages (OBP) and team performance, as opposed to traditional statistics such as batting averages. By exploiting market inefficiencies through these advanced data analytics, the Athletics were able to compete for the championship despite budget constraints. Following the release of Moneyball, MLB teams adjusted their player valuations, leading to a league-wide reassessment of players' market value to accord with OBP (Hakes & Sauer, 2006). This demonstrates the disruptive potential of big data and advanced data analytics in professional sports.

Moneyball triggered a shift toward analytics-driven decision-making in sports, including football (soccer). Clubs like Brentford FC in England and FC Midtjylland in Denmark became recognized for adapting the Moneyball concept to football scouting, utilizing advanced metrics to identify undervalued talent. However, applying Moneyball-like concepts to football presents significant challenges, primarily due to the sport's complexity, fluidity, tactical variability, and high level of interdependence among players (Gerrard, 2007). Unlike baseball, where player contributions can be examined in isolated matchups, football requires a more complex, integrated, and context-aware performance evaluation.

In recent years, football clubs have been adopting more sophisticated metrics to assess player performance and team success (Brechot & Flepp 2020). Short-term match outcomes are influenced by randomness, leading to systematic misjudgments in decision-making. This points to the complexity of data analytics and decision-making in football. Three barriers for data analytics in football have been identified: technological, conceptual, and cultural barriers

Gerrad, 2016). Although technology has evolved, football teams still make costly mistakes in recruitment.

While a few clubs have had success applying Moneyball-like analytics to football scouting and transfer market decisions, existing models rely on basic statistical indicators such as goals, assists, and pass completion rates. These metrics might not be able to fully capture player contributions, particularly in roles that require tactical intelligence, defensive organization, or pressing efficiency (Hughes et al., 2012). Additionally, transfer market inefficiencies persist, with clubs frequently overpaying for players based on short-term performance trends (Essien et al., 2024).

Short-term performance fluctuations such as winning or losing streaks also often lead to misguided transfer decisions and managerial changes, as clubs fail to account for the underlying expected performance (Brechot & Flepp, 2020). Similarly, studies applying data envelopment analysis (DEA) to player valuation highlight that some players are significantly over- or under-valued based on non-contextualized statistics (Essien et al., 2024; Gavião et al., 2019).

AI and ML offer a way forward, providing deeper, multi-dimensional player analysis, including more context-aware factors. AI-driven scouting models can incorporate predictive analytics to forecast future player development, optimize recruitment strategies, and reduce inefficiencies in transfer market decision-making.

But despite the increasing role of analytics in football, AI-driven models remain underexplored in the context of scouting, talent identification, and performance analytics. Although existing studies have explored alternative key performance indicators (KPIs) for different positions (Hughes et al., 2012) and evaluated efficiency using data-driven models (Gavião et al., 2019), there is a lack of research on how AI might improve scouting, performance evaluation, and market efficiency.

Furthermore, football clubs resist fully data-driven recruitment strategies due to cultural barriers and a high degree of uncertainty (Essien et al., 2024; Gerrard, 2016). Adopting AI in football analytics raises questions regarding its disruptive potential. Given these challenges, this thesis seeks to address the following Research Question:

How can AI disrupt football scouting, and which adoption dynamics influence its implementation?

To answer this question, this study examined emerging AI-driven scouting and performance analytics methods. We conducted expert interviews to assess current applications, limitations, and expectations of AI in professional football scouting and performance analytics. Lastly, through a survey, we sought to understand the implications of data-driven decision-making on fan engagement in an emotionally charged sport such as football.

2 Literature Review

The literature review provides context for our analysis of AI’s impact on data analytics in football. We explore traditional scouting and performance analytics, discuss the rise of AI, its adoption, and future implications for this domain. Lastly, we present relevant management theories.

2.1 Introduction to the football industry

Football is the most popular sport globally, with 43% of the population expressing interest in the sport (Nielsen Sports, 2018). Professional football is a multibillion-dollar industry, attracting the attention of various regulators and economic stakeholders. This increasing importance is reflected in economic-managerial scientific techniques that have been applied to the football industry (Renzi & Taragoni, 2023). Operating in a multi-level ecosystem, the football industry’s impact extends to economic, social, and cultural levels (Yiapanas et al., 2024).

The European football market grew from €28.9 bn in 2018/19 to €35.3 bn in 2022/23 and is projected to reach €39.1 bn in 2024/25 (Deloitte, 2024). Focusing on the combined revenue of the ‘big five’ European league clubs, England, Germany, Spain, Italy, and France, the dimensions become even more evident. An increase in the aggregated club revenue from €12.06 bn to a projected €20.70 bn in 23/24 reflects a relative increase of 71.64% in just a decade.

Despite growth, football remains a structurally unstable industry. Due to high wage-to-revenue ratios and unsustainable transfer spending, many clubs operate at a financial loss (Renzi & Taragoni, 2023). With increasing competition and the rise of modern technology, clubs are increasingly integrating data analytics into scouting, player valuation, and tactical planning to gain a competitive advantage (Deloitte, 2024). Reflecting the need for more sustainable data-driven decision-making in football.

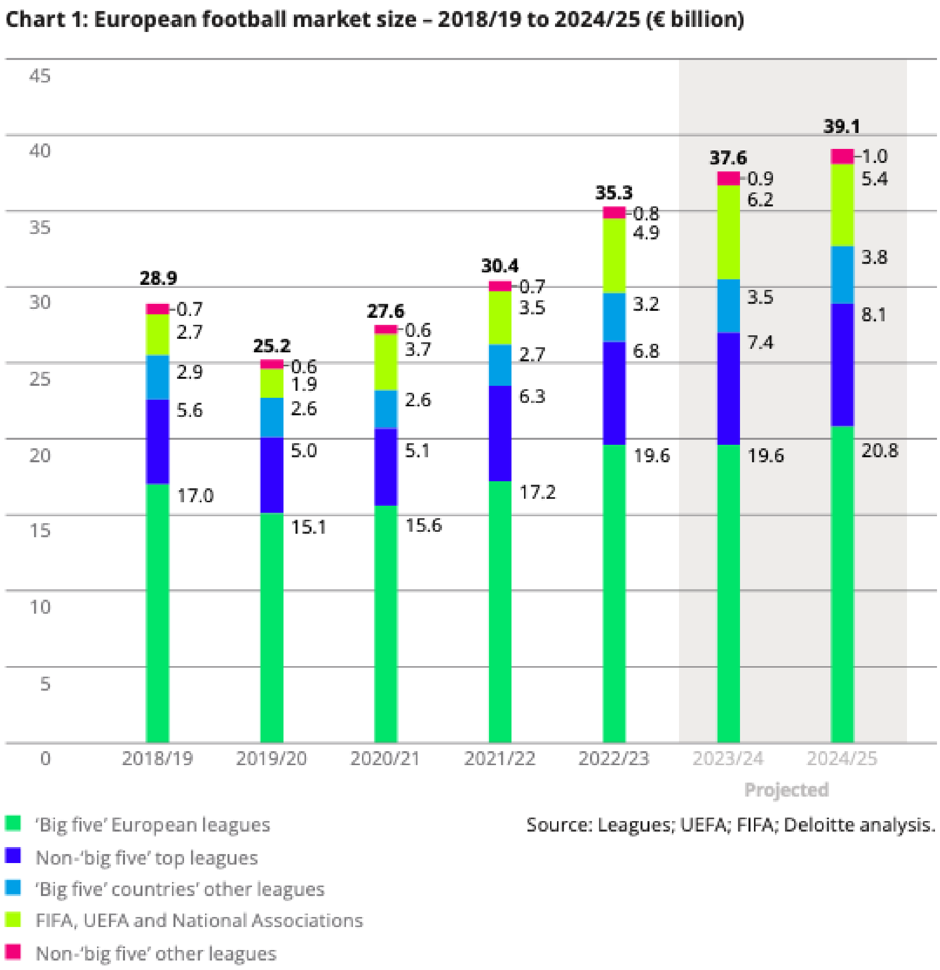

Figure 1: European Football Market Size – 2018/19 to 2024/25 (€ billion) (Deloitte, 2024)

2.2 The Moneyball Approach

The MA originated in MLB, notably employed by the Oakland Athletics (Lewis, 2004). It is closely associated with the team's General Manager, Billy Beane, who implemented innovative, data-driven methods (Herberger & Litke, 2021). Facing a significantly lower budget than competitors, the Athletics adopted a 'David' approach, leveraging unconventional, quantitative analytics to compete effectively (Gerrard, 2016).

Central to this approach was sabermetrics, the statistical analysis of baseball data, which identified market inefficiencies and undervalued players, notably emphasizing OBP over traditional batting averages, which failed to accurately capture a player's contribution to winning. Oakland's success, including a 20-game winning streak despite limited resources, exemplifies the strategy's efficacy in outperforming expectations (Gerrard, 2016; Herberger &

Litke, 2021). The MA detailed in Lewis's (2004) book and subsequent film, has significantly influenced sports analytics globally (Herberger & Litke, 2021).

The MA's application to more complex sports like football is limited by challenges in data collection and analysis due to continuous gameplay and multifaceted player roles, alongside technological, conceptual, and cultural barriers (Gerrard, 2007; Torgler, 2023). The relative simplicity of baseball's discrete events facilitated early adoption of data analytics, a process more complex in sports with ongoing, interdependent events.

2.3 Applying Moneyball Principles in Football

Although the MA has been extended to football and other sports (Gavião et al., 2019), directly transferring its principles to complex invasion team sports like football presents unique challenges (Gerrard, 2007; Gerrard, 2016). Unlike baseball, which is naturally discrete and where individual contributions are easily quantifiable, football involves actions away from the ball and in non-linear contexts that are difficult to measure but significantly influence match outcomes (Bornn et al., 2018; Herberger & Litke, 2021).

Applying MA in football involves strategic player acquisition and team management through statistical analyses and data-driven decision-making (Chatziparaskevas et al., 2024). Similar to the Oakland A's, this data-driven management approach offers a means for financially constrained clubs to compete successfully with wealthier opponents (Chatziparaskevas et al., 2024). Factors such as anticipated efficiency and effectiveness gains, and fans' perception towards the technology influence the adaptation of Moneyball principles (Plattfaut & Koch 2021). In football, Brentford FC's successful promotion to the Premier League (PL) using advanced statistical indicators despite limited resources is often seen as an example of successfully implementing Moneyball principles in the sport (Chatziparaskevas et al., 2024). While the core concept of data utilization is transferable, adapting Moneyball to football requires acknowledging the sport's complexity (Gerrard, 2007; Reade & Royle, 2025).

2.4 Football Scouting and Performance Analytics

Recent advancements have significantly increased the use of data analytics in professional football, particularly in performance analyses and scouting (Biermann, 2019; Goes et al., 2021; Link, 2018). Historically, tradition, experience, and intuition were crucial in football management and strategy. Coaches and managers predominantly based key decisions on their understanding of the game, built over years of experience (Mackenzie & Cushion, 2013; Reade & Royle, 2025; Rein & Memmert, 2016).

2.4.1 Traditional Scouting vs Data-Driven Scouting

Player scouting has traditionally relied significantly on subjective observations and scouts' experience (Hughes et al., 2012; Schmidt, 2020). While valuing expertise, this approach is limited by individual biases and memory constraints, which can hinder objective assessment (Andrews, 2022). In contrast, the MA in baseball demonstrated the potential of data-driven management to identify undervalued talents and gain competitive advantages through extensive data analyses (Patnaik et al., 2019). The modern reality of football transfers has increasingly shifted towards reliance on data, exemplified by clubs like Brentford, which leverage analytics for recruitment success against larger, less data-driven competitors (Raza, 2025). Advances in data availability and analyses have facilitated a shift toward data-driven scouting, utilizing diverse sources and analytical techniques to evaluate (Herberger & Litke, 2021; Link, 2018). Rather than depending on scouts' intuition, teams increasingly incorporate sports analytics technology into talent identification, enabling pattern-based analyses of complex player performance over time (Araújo et al., 2021; Link, 2018; Schmidt, 2020).

Statistical analyses of in-game situations increasingly influence talent identification and player recruitment (Gavião et al., 2019). Data analysis may help identify technical qualities in players who might be undervalued or overlooked by the traditional market (Gavião et al., 2019). Although data mining approaches can support strategic planning, coaches ultimately seek to retain decision-making authority (Herberger & Litke, 2021).

2.4.2 Evolution of Football Performance Analytics

Football performance analyses have advanced beyond simple observational data and statistics, such as shots on goal, passes, tackles, possession, distance covered, and heat maps (Link, 2018; Rein & Memmert, 2016). Early tactical analyses relied on variables that overlooked significant contextual information (Rein & Memmert, 2016). The field has progressively shifted from simple on-ball metrics to more sophisticated, contextually-rich analytical methods (Bornn et al., 2018).

The advancement of digital technologies and sensor systems has significantly increased data availability, particularly spatio-temporal position data, which is now standard in professional football and offers detailed performance insights (Link, 2018). Public datasets, such as those from Wyscout, result from meticulous video analyses involving multiple steps: recording initial player positions and formations, detailed event labeling with specific types and subtypes (E.g., a pass as a header or free-kick), and quality control through automated algorithms and manual verification, ensuring data reliability and validity (Zeng & Pan, 2021). This increasing data size is a notable trend in sports science (Rein & Memmert, 2016).

New methodologies extract meaningful insights from large datasets, focusing on identifying patterns, structure, and causal relationships to deepen understanding of sports performance. Sophisticated performance indicators include modeling interactions using dynamic systems theory concepts like Approximate Entropy and Relative Phase (Link, 2018). Network analyses have been employed to analyze passing patterns linked to success, leading to tactical constructs like Control of Space, Availability, Pressing, and Dangerousity, derived from spatiotemporal tracking data (Gavião et al., 2019; Herberger & Litke, 2021; Rein & Memmert, 2016). Newly introduced metrics, including Expected Goals (xG), Expected Assist (xA), and Expected Goal Involvement (xGI), provide probabilistic assessments of scoring opportunities based on contextual factors (Chatziparaskevas et al., 2024; Pu et al., 2024). Performance indices, like the Player Performance Efficiency Index (PEI), aim to objectively evaluate player performance across technical dimensions (Essien et al., 2024). Further, metrics such as Expected Threat (xT) evaluate the contribution of passes and carries in advancing play towards goal, while the broader framework of Expected Possession Value (EPV) quantifies the instant value of each moment in a possession by analyzing detailed spatiotemporal data of all players and potential actions (Fernández et al., 2019; Wisdom & Javed; 2023). A recurring key idea in tracking data analyses is pitch control, which quantifies the space dominated by players or teams, offering insights into tactical dynamics like counter-attacks versus defensive depth (Graham, 2019).

Despite advancements in sophisticated football metrics, effectively communicating data-driven insights to coaching staff remains a challenge, particularly with complex or opaque models known as ‘black boxes.’ This has led to increased focus on Explainable AI (XAI) and methods that translate complex numerical outputs into actionable, contextually relevant insights for practitioners (Rahimian et al., 2025).

The increasing volume, variety, and velocity of this data have sparked discussions on big data in sports analytics (Goes et al., 2021; Herberger & Litke, 2021). Although football datasets may not reach the petabyte scales typical of big data, effective management of such heterogeneous data necessitates specialized solutions beyond traditional methods (Araújo et al., 2021; Rein & Memmert, 2016).

2.4.3 The Role of AI in Football Scouting and Performance Analytics

AI is increasingly recognized as transforming sports analytics and football (Chatziparaskevas et al., 2024), with ML being a key component of this transformation. (Herberger & Litke, 2021). AI and ML are significantly extending the capabilities of football analytics, moving beyond traditional statistical methods (Tuyls et al., 2021).

AI is progressively utilized in scouting and player evaluation through ML models that assist in player rankings, salary decisions, and talent identification (Schmidt, 2020). AI is expected to be capable of synthesizing scouting reports, advanced game statistics, performance testing, training loads, injury reports, and personality profiles to predict how players might develop and identify potential talents (Schmidt, 2020). For instance, PLAIER has constructed an extensive database integrating event data, injury data, and salary data from over 100 leagues, providing guidance on transfers, assessing squad cohesion, informing coaching decisions, quantifying expected individual player impact on team performance, and identifying optimal transfer targets (Bate, 2025). Further, top clubs employ AI-driven applications to scout emerging talent (Bantock, 2024). This integration of data and AI is seen as a fundamental shift in football management (Chatziparaskevas et al., 2024; Pu et al., 2024).

AI and ML technologies detect complex patterns and quantify previously unmeasurable aspects of game dynamics and player performance, surpassing traditional subjective assessments and basic statistics (Schmidt, 2020; Memmert & Rein, 2018). These advanced approaches facilitate tactical decision-making models (Rein & Memmert, 2016). For example, AI systems can simulate a game against all PL clubs 100,000 times to estimate a potential player’s impact and fit, a task unfeasible manually (Bate, 2025). This enables predicting player performance across multiple player-level metrics, accounting for differences in playing style, teammate ability, and league quality (Dinsdale & Gallagher, 2022). ML approaches like neural network modeling and Kohonen Feature Maps (KFM) have been used to study tactical patterns and identify team formations (Link, 2018). Predictive models based on Back Propagation neural networks aid in determining optimal player positions by analyzing performance and physiological data, thus supporting objective player selection and recruitment strategies, moving beyond subjective coach perceptions and allowing for objective targeting of team deficits (Zeng & Pan, 2021). Deep learning algorithms can imitate tactical behavior and estimate team strategies in various situations (Link, 2018). AI-driven predictions extend to estimating player talent, market value, injury risk, and identifying undervalued players, thereby informing transfer decisions and training load management (Gavião, 2019; Sulimov, 2024).

Advanced AI models analyze spatial value on the pitch using continuous player-tracking data, enabling estimation of defensive control and strategic positioning. These methods identify key spaces and complex patterns for tactical decisions and player evaluation (Bornn et al., 2018). Leveraging ML techniques supports strategic planning and tactical decision-making at both individual and team level (Herberger & Litke, 2021; Rein & Memmert, 2016). Technological advancements allow for real-time data availability on smart devices, facilitating rapid decision-making with increased reliance on data scientists within coaching staffs (Herberger & Litke, 2021). Network analysis, often combined with machine learning techniques like K-means clustering, is used to analyze player passing networks and suggest in-game strategies. Clustering analysis is also used to identify technical performance indicators for various positions and evaluate overall performance (Gavião, 2019).

AI enhances accessibility in football analytics through recent advancements like 'wordalisations,' which utilize large language models (LLMs) to translate complex model outputs into natural language explanations. This approach addresses the communication gap between technical data and practical, narrative-driven understanding for coaching staff (Rahimian et al., 2025). Tools such as Twelve Football's Earpiece provide football intelligence and data-driven insights via WhatsApp, translating complex data into actionable narratives for sporting directors, analysts, and coaches, thereby facilitating recruitment and performance evaluation processes without the need for complex dashboards or manual data analysis. This exemplifies a trend towards more user-friendly and readily available analytics for decision-makers across all levels of professional football (Carey, 2025).

Thus, AI significantly impacts football analytics and serves as a benchmark for AI research (Pu et al., 2024). The availability of large amounts of data has driven ML's breakthrough and paradigm shifts (Herberger & Litke, 2021). Future AI models are expected to integrate new parameters, such as psychological profiles and injury prediction, expanding their operational scope in football (Bate, 2025). AI is transforming both on-pitch activities (match analysis, performance analysis) and club management (scouting, decision-making) (Chatziparaskevas et al., 2024).

2.5 Overcoming Limitations of the Moneyball Approach with AI

While the MA demonstrated the value of data in baseball, its application in complex team sports like football faces challenges, which AI and big data can help overcome (Gavião, 2019; Reade & Royle, 2025).

Conventional football analytics, often relying on basic statistics or observational data, are limited by the game's dynamic and non-linear nature, reducing their usefulness for strategy and performance assessment (Biermann, 2019). Early tactical analyses frequently overlooked valuable contextual information (Rein & Memmert, 2016). The complexity and fluidity of football have historically hindered the applicability of traditional statistical approaches, with some early data efforts failing to correlate with game outcomes, especially regarding off-ball actions (Biermann, 2019; Bornn et al., 2018; Gavião, 2019).

The main challenges in football analyses involve the subjectivity of human assessments, which AI mitigates by offering objective, data-driven insights, reducing reliance on individual perception (Andrews, 2022; Carey, 2024). Due to football's complexity, characterized by numerous players, dynamic interactions, and low scoring, traditional statistics often provide limited perspective. AI's ability to detect intricate patterns in high-dimensional data is crucial in this context (Tuyls et al., 2021). Deep learning models can analyze spatiotemporal tactics, evaluating actions within their broader tactical framework rather than as isolated events (Fernández et al., 2019). Big data and AI address Moneyball's limitations by managing vast, diverse datasets, enabling more comprehensive analyses than conventional methods (Herberger & Litke, 2021; Rein & Memmert, 2016).

AI models, such as PLAIER, focus on system efficiency, assessing individual contribution to team success rather than isolated attributes, thus enhancing player valuation (Bate, 2025). Enabling a more precise identification of undervalued players extends the core Moneyball principle of exploiting market inefficiencies into previously unmeasurable dimensions of football performance. Advanced techniques like random forest and predictive analysis facilitate the development of increasingly sophisticated models to assist in strategic planning and forecast outcomes or performance (Herberger & Litke, 2021). AI enables the analysis of tactical behavior across several levels (individual, group, team) and may potentially address the existing gap in comprehension of the interplay of factors such as formations, individual skills, and physiological demands (Rein & Memmert, 2016). Geometric models and metamodels, combined with data on player position and game status, enable the definition of strategies and playing styles based on underlying tactical constructs (Herberger & Litke, 2021). Moreover, technological advancements allow for the integration of broader datasets, improving the identification of undervalued players and addressing limitations of traditional scouting and metrics (Gavião, 2019; Schmidt, 2020).

A particularly disruptive insight facilitated by AI in football management challenges the perception of a coach's impact on team success. Recent AI analyses suggest that team success is determined approximately 90% by player quality, and 10% by coaching impact, though this seemingly minor influence can be decisive. This re-evaluates the significance of a team's player quality in recruitment decisions. For instance, AI analyses indicated that Thomas Tuchel's dismissal from Chelsea was not necessary, as his performance matched the squad's inherent quality. Similarly, AI models showed that Jürgen Klopp's achievement at Liverpool was consistent with expected results based on team strength, rather than overperformance. These findings provide stakeholders with a data-driven perspective, supporting more informed decision-making in club management (Bate, 2025).

Despite these advancements, AI in football still faces limitations due to inherent randomness and data constraints, which introduce uncertainty into predictions. For instance, while a BP neural network model for player position prediction achieved an overall accuracy of 77%, performance varied by position. Precision was higher for midfielders and defenders (77% and 90%), but significantly lower for attackers (around 40%), primarily due to disparities in dataset size and imbalance.

The effectiveness of ML models is often constrained by data size and the technical complexity of AI algorithms, such as computational demands (Zeng & Pan, 2021). Data scarcity is particularly relevant for low-data players, emerging talents, or recently promoted teams

(Dinsdale & Gallagher, 2025). The 'Transfer Portal' model mitigates this issue through the use of 'adjustment models' that estimate initial performance levels, updating them as more data becomes available. This approach facilitates more informed transfer decisions, even with limited game data (Dinsdale & Gallagher, 2025). Predictions remain further uncertain due to intrinsic randomness, technical limitations, and limited sample size of matches (Araújo et al., 2021).

One of the key challenges in football analytics is bridging the communication gap between complex data analyses and the practical understanding of coaching staff (Rahimian et al., 2025). Coaches need actionable insights that are often not provided by numerical probabilities or metrics alone. AI-driven solutions like 'wordalisation' help translate these outputs into natural language narratives by leveraging LLMs and making insights more accessible and useful (Rahimian et al., 2025). While there is a trade-off between engagement and accuracy in automated descriptions, a comprehensive wordalisation approach, incorporating contextual examples and narrative elements, effectively balances these factors, enhancing practical utility (Rahimian et al., 2025). This transformation reduces reliance on intuition, which has historically impeded data integration in football (Tuyls et al., 2021). Additionally, AI automates data engineering tasks, improving efficiency and democratizing access to strategic information among decision-makers like chairmen or sporting directors (Carey, 2025). The success of clubs like Liverpool FC exemplifies how synthesizing human expertise with AI, referred to as 'integrated intelligence,' can foster a sustainable competitive advantage (Lichtenthaler, 2020).

Although initial skepticism persisted, top coaches like Jürgen Klopp have embraced data-driven approaches after experiencing their benefits (Lichtenthaler, 2020; MIT Sloan Sports Analytics Conference, 2024). Nevertheless, successful AI integration in football clubs depends on stable leadership, funding, and overcoming cultural resistance, including distrust of data that conflicts with entrenched beliefs or subjective judgments (Tuyls et al., 2021). Addressing data-centric and technical limitations remains crucial for unlocking its full disruptive potential in football. Cultural barriers, such as managers' concerns about negative fan perceptions, further hinder adoption in traditional clubs (Plattfaut & Koch, 2021).

The adoption of AI-driven insights among clubs varies significantly; some use it as a critical filter to target players, others for validating proposed signings, and more advanced teams for generating direct player recommendations, indicating embedded strategies despite cultural barriers (Bate, 2025). While AI's application in football is not entirely novel, there is a need for greater understanding of its strategic implementation, challenges, and cultural resistance from a management perspective.

2.6 Key Concepts of Innovation

2.6.1 Disruptive Innovation

Christensen's notion of disruptive innovation explains how market and technological paradigm shifts can cause established firms to fail (Christensen, 1997). He distinguishes between sustaining and disruptive innovation, where the former pertains to improving existing products along dimensions valued by mainstream customers. Disruptive innovations, on the other hand, introduce novel attributes such as simplicity, affordability, or accessibility. They often underperform in traditional performance metrics and appeal in particular to overlooked or entirely new customer segments (Christensen, 1997; Christensen et al., 2018).

Disruptive innovations typically enter markets at the low end or in new markets with unattractive margins, leading incumbents to overlook them (Christensen et al., 2018). Over time, these innovations improve and capture mainstream markets, displacing incumbents who fail to respond. An outcome driven not by managerial incompetence but by rational decisions favoring profitable, sustaining innovations (Christensen, 1997; King & Baatartogtokh, 2015).

2.6.2 Diffusion of Innovations

The Diffusion of Innovation model developed by Rogers (2003) provides a fundamental framework for understanding how new ideas, technologies, or practices are adopted within a social system over time. Diffusion is defined as the process by which an innovation is communicated through specific channels among members of a social system (Rogers, 2003).

The framework defines five innovation characteristics that influence the adoption rates: relative advantage, compatibility, complexity, trialability, and observability. Innovations perceived as offering greater benefits compared to existing solutions (relative advantage), aligning well with users existing values and experiences (compatibility), being easy to understand and use (low complexity), allowing for experimentation (trialability), and producing visible results (observability) tend to be adopted more rapidly (Lou & Li, 2017; Robinson, 2009; Rogers, 2003).

Rogers categorizes adopters into five categories based on their readiness to adopt innovations: innovators, early adopters, early majority, late majority, and laggards. These segments follow a bell-shaped distribution and reflect varying levels of innovations and risk tolerance, which are critical for diffusion planning (Rogers, 2003).

Diffusion of Innovations emphasizes the significance of interpersonal communication and social networks in shaping adoption decisions. Peer influence is often decisive in reducing uncertainty and encouraging behavioral change, particularly among later adopters (Robinson, 2009). As such, beyond dealing with technological adoption, the theory also examines broader patterns of social change.

2.6.3 Blue Ocean Strategy

Blue Ocean Strategy (Kim and Mauborgne, 2005) is a transformative view of strategy that shifts attention from competitive rivalry to the creation of uncontested market space. Instead of competing with the constraints of existing industries 'red oceans,' firms should seek out 'blue oceans' defined as new uncontested market spaces where competition becomes irrelevant (Kim & Mauborgne, 2005; Kim & Mauborgne, 2005b). Unlike traditional views that assume fixed industry boundaries, this view implicates market reconstruction through strategic action (Kim & Mauborgne, 2005).

Value innovation is at the core of Blue Ocean Strategy. Firms that succeed in creating blue oceans do so by delivering a leap in value for both the company and its customers, often by redefining industry norms and eliminating assumptions (Kim & Mauborgne, 2005b; Kim & Mauborgne, 2005c). This demonstrates that the perceived trade-off between value and cost can be overcome by aligning innovation with utility, price, and cost structures (Kim & Mauborgne, 2005).

2.6.4 Dynamic Capabilities

The dynamic capabilities framework, introduced by Teece, Pisano, and Shuen (1997), provides a conceptual understanding of how firms compete in rapidly changing environments. Dynamic capabilities refer to a firm's ability to integrate, build, and reconfigure internal and external competencies to respond to market changes. Unlike the static resource-based view (RBV), which emphasizes valuable, rare, inimitable, and non-substitutable (VRIN) resources, the dynamic capabilities approach explains how firms adapt these resources over time to maintain relevance in dynamic contexts (Eisenhardt & Martin, 2000; Teece et al., 1997).

These capabilities are embedded in organizational and strategic routines, such as product development, strategic decision-making, and alliance formation (Eisenhardt & Martin, 2000). By acquiring, recombining, and redeploying assets, firms can innovate and respond more effectively to market disruptions, especially in high-velocity contexts where active disruption of conventional bases of persistent advantage exists (Barreto, 2010; Samsudin & Ismail, 2019; Teece et al., 1997). Although dynamic capabilities can provide temporary advantage, their ultimate value depends on their strategic application and ongoing renewal, making them necessary but not solely sufficient for sustained competitive success (Collis & Anand, 2019).

3 Methodology

3.1 Research Design

The research design aimed to assess AI's disruptive potential in football. Figure 2 illustrates the methodology.

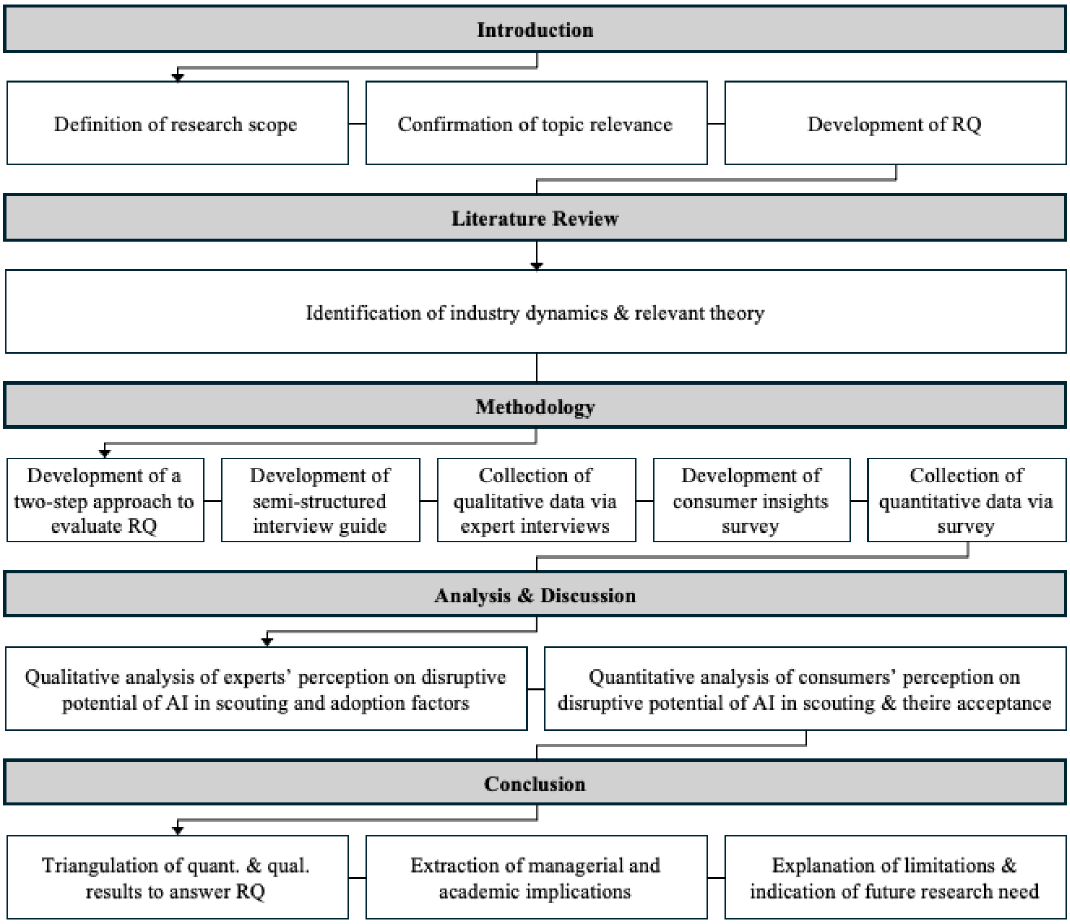

Figure 2: Research Design

A mixed-methods approach using triangulation, combining quantitative and qualitative data with both inductive and deductive thinking, was selected (Mayring, 2014; Sekaran & Bougie, 2016). Data were collected through semi-structured interviews with industry experts, providing in-depth insights (Qu & Dumay, 2011; Rowley, 2012). Additionally, a survey assessing fan perceptions and technology acceptance, considering fan perception as a key adoption factor identified in the literature, was conducted. Triangulation integrated qualitative analyses, literature review, expert interviews, and survey results to synthesize findings.

3.2 Data Collection

Primary data was collected through two sources, semi-structured expert interviews and a consumer survey.

3.2.1 Primary Data Collection – Expert Interviews

Interviews are a fundamental method in qualitative research, providing valuable insights into individuals' experiences and perspectives (Doody & Noonan, 2013; Glaser & Strauss, 2017). For this exploratory study, semi-structured interviews were selected due to their balance of structure and flexibility, facilitating in-depth exploration of complex topics (Barriball & While, 1994). Engaging with knowledgeable respondents or key personnel allowed for detailed data collection and richer understanding (Glaser & Strauss, 2017). Semi-structured interviews are particularly suitable for capturing perceptions on complex and sensitive issues, enabling probing for clarification and elaboration (Barriball & While, 1994). It prioritizes participants' unique perspectives over generalization (Adeoye-Olatunde, & Olenik, 2021).

An interview guide was used to standardize data collection and provide structure, incorporating open-ended and follow-up questions to enhance depth (Adeoye-Olatunde, & Olenik, 2021; Barriball & While, 1994; Doody & Noonan, 2013). Probing can lead to new concepts emerging, which increases richness of data for analysis (Doody & Noonan, 2013). The guide consisted of 12 core questions (cf. Appendix I), with interviews averaging about 36 minutes, allowing flexibility for participant expertise while maintaining consistency. In total, twelve interviews were conducted, including one in written form, ensuring data saturation, which typically occurs with twelve interviews (Guest et al., 2006).

Table 1 - Overview of Interviewees

ID	Short Description
E1	Data & AI Recruitment Specialist with over 16 years of experience in technical recruitment, specializing in data engineering and analytics within the financial services industry, and increasingly focusing on the football and rugby industries in recent years
E2	PhD researcher specializing in AI and football analytics with 4 years of experience in AI applications in football
E3	Consultant with over 4 years of experience helping football clubs become data-driven in scouting and recruitment, with expertise in digital strategy, innovation, and strategy
E4	Professional scout and analyst with 11 years of experience in top-tier football, including work across La Liga and the Premier League, specializing in integrating AI and data-driven approaches
E5	Football data scientist with over 6 years of experience in football analytics, working across the top leagues of Italy, Portugal, and the Netherlands
E6	Data scientist at one of the top four Portuguese clubs, with a background in computer science and data engineering
E7	Professional football scout at one of the Big Six clubs in the Premier League with over 10 years of experience in European football across top clubs in Germany and Austria
E8	Football data science consultant with over 3 years of experience in AI and predictive modeling for player movement and scouting
E9	Lead recruitment analyst at a Premier League club with over 3 years of experience in football recruitment and analysis. Previously worked with various English clubs
E10	Chief Data Officer at a football data analytics company with over three years of experience in football data science and former Director of Data at one of the Big Six clubs in the Premier League
E11	Data manager at one of the top four Portuguese clubs with over 3 years of experience in implementing data-driven strategies across various departments
E12	Football data scientist at one of the two biggest Spanish clubs, with several years of experience in data analytics

3.2.2 Primary Data Collection – Consumer Insights Survey

Survey data can be generated rapidly and in large quantities using online platforms (Ball, 2019). The questionnaire covered demographics, perceived usefulness and trust in AI, authenticity concerns, cultural resistance, AI acceptance, and its disruptive potential. Conducted online through Qualtrics, the self-administered format minimized social desirability bias and ensured consistency in question delivery (Ball, 2019).

Twenty-two Likert scale questions were included, with Question 9_4 serving as a control to ensure data quality. In total, 170 respondents began the survey, and 125 completed it. Of these, 7 did not pass the control question and 12 respondents were excluded based on screening criteria (how closely they follow football), resulting in a final sample size of 106 respondents.

Fan perceptions of AI in football scouting and performance analyses were examined using an extended Technology Acceptance Model 3 (TAM3), incorporating constructs such as Perceived Authenticity, Trust in AI, and Cultural Resistance. TAM3's robustness in explaining technology acceptance, especially its adaptability in non-user contexts and those involving emotional and cultural factors, justified its selection.

Traditionally, TAM focuses on Perceived Usefulness and Ease of Use as predictors of Behavioral Intention for understanding user acceptance of technology (Davis, 1989). The extended TAM3 framework allows for nuanced understanding by including antecedents and moderators suitable for more complex contexts (Venkatesh & Bala, 2008).

Given that football fans are not direct users but are impacted by its outcomes as major drivers of the football industry, TAM3 was adapted by replacing Behavioral Intention with Acceptance (support for AI use) and Behavioral Response (changes in fandom engagement). This approach aligns with prior research on non-user stakeholders affected by technology (Straub, 2009; Quershi, 2022). Trust was deemed a critical factor based on existing literature (Gefen et al., 2003).

Alternatives such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Theory of Planned Behavior (TPB) were considered but deemed less suitable due to their complexity or lack of technological specificity (Ajzen, 1991; Venkatesh et al., 2003). TAM3's prior application in sports contexts (Capasa et al., 2022; Mahardika & Suhari, 2023) further supported its use.

To address the emotional and cultural dimensions of football fandom, particularly concerns about AI diminishing the human element or breaking traditions, TAM3 was extended with three constructs and dual outcome measures:

> **Perceived Authenticity:** Measured perceptions that AI undermines football's human nature. Authenticity is a core driver of fan engagement in sports, influencing acceptance of technological interventions and innovations (Numerato, 2015).

Trust in AI: Assessed confidence in AI's reliability and accuracy. Especially in high-stakes domains, Trust is a significant determinant of technology acceptance (Kim et al., 2023).

Cultural Resistance: Captured opposition to AI due to conflicts with traditional values. Football fans often see technological changes as damaging the cultural heritage of football (Numerato, 2015).

Acceptance and Behavioral Response: Acceptance measured attitudinal support for AI use, while Behavioral Response assesses changes in fandom engagement. This dual approach reflected fans' non-user status and engagement dynamics, adapting TAM3 to capture both attitudinal and behavioral outcomes in response to AI adoption.

These extensions addressed managers' concerns about negative fan engagement, which is a key driver for successful adoption of data-driven and AI-based models in football scouting.

4 Results

4.1 Expert Interviews

This chapter presents the empirical results of the study. Section 4.1 reports the findings from the expert interviews, while section 4.2 outlines the results from the consumer survey.

4.1.1 Current Data Science Practices & Understanding

4.1.1.1 Integration of Traditional Scouting and Data

Integrating data science in sports was widely recognized as a significant development. Similar to the literature, [E7] noted a rapid evolution of data integration in scouting in recent years [E4] underlined that 'if you don't open up to data analysis, nowadays you cannot compete.' Likewise, [E7] declared data integration as 'absolutely necessary,' especially for clubs in international contexts. However, adoption varies significantly across clubs, leagues, and geographies, with the first two to three English leagues perceived as the most advanced [E3, E5, E6, E7, E8, E9, E10, E11]. Some experts further indicated that not all, or even most, clubs have implemented data science into their approaches [E3, E5, E6, E7, E8], noting that especially smaller clubs lag in data integration due to cost, ownership structures, internal resources, and distrust. [E11] stated that, particularly in Portugal, some clubs don't even have dedicated scouting departments, making it 'hard to justify having a data department.' In contrast, some experts stated that nowadays most clubs use data science to complement scouting [E4, E10] and 'the smaller the club, the more important it is that data is utilized' [E10].

Data science is predominantly used to enhance efficiency and reduce bias in scouting. Its primary application is for identifying and early filtering of players [E3, E5, E6, E7, E8, E9, E11, E12]. [E6, E11] also noted that data is used both ways, including later to validate players identified by traditional scouts. [E10] suggested a dual approach, creating separate shortlists via scouts and data in parallel to challenge each other. Data is crucial and integrated into the decision-making process to complement scouting, enabling more informed decisions [E3, E4, E5, E6, E7, E9, E10, E11, E12]. Some interviewees stated that their clubs would never sign a player without data supporting the player choice [E4, E5, E11].

4.1.2 AI & ML Usage and Applications in Football Scouting

4.1.2.1 Variance in AI and ML Adoption

While interest in AI is growing, many professional clubs have yet to fully integrate sophisticated solutions. Adoption levels vary greatly, as it is with regard to distinct perceptions among industry experts. Some experts called AI a 'buzzword' with limited deep implementation [E3]. ML and AI are generally the next step after structured data integration, but only ~20% of clubs with structured data have advanced to predictive and robust ML models [E8]. [E5, E7, E9, E11] indicated low AI use in scouting, with most clubs not employing sophisticated models daily and in decision-making. In contrast, [E4] commonly uses AI and stated that almost every professional club has started to use AI processes. [E1, E2, E6, E7, E10, E11] acknowledged that existing sophisticated models are primarily deployed in performance evaluation rather than decision-making. The football industry was widely described as highly closed domain, making it hard to gauge actual adoption, as clubs keep models and discoveries confidential [E2, E3, E4, E6, E8, E10]. The uneven spread of AI within football and experts advocating for cautious use until effectiveness is proven, maps directly onto Rogers' Diffusion of Innovation model (2003) and its different readiness categories for adopting innovations.

4.1.2.2 Current Use Cases and Applications

AI is most often applied to improve efficiency in scouting, acting as a filter to generate player shortlists from large datasets, reducing initial scouting efforts, and facilitating more focused traditional human scouting as a subsequent step [E1, E2, E4, E5, E7, E8, E9, E10, E11]. ML models help determine key metrics for specific positions [E5], and [E9] described leveraging AI at his PL club to condense multiple scouting reports.

Beyond shortlisting, AI supports advanced player evaluation. It allows to quantify more sophisticated on-ball and off-ball metrics such as defensive pressure, player movement, and impact on game outcomes, which are difficult to assess with conventional methods [E2, E4, E10]. More uniquely, [E4] described developing proprietary AI models within the coaching staff, trained on tailored data to analyze player movements on specific tactical concepts, predicting customized player-system compatibility based on the team's specific needs. Other experts highlighted ongoing work on predicting performance across leagues and systems to anticipate players' adaptations [E1, E3, E4]. Further applications included injury prevention and youth player development [E2, E7, E8].

All experts [12E / 12E] emphasized the need to balance AI insights with human judgment, especially for intangibles like leadership, mentality, personality, and off-pitch factors, where AI currently falls short [E1, E2, E5, E6, E7, E9, E10, E11]. AI was highlighted as a vital complement in the scouting process, not as a replacement for traditional scouts

4.1.3 Drivers and Opportunities for AI Adoption in Football Scouting

Experts identified several key drivers and opportunities for AI adoption in football scouting, highlighting its potential to enhance efficiency, precision, and strategic decision-making.

4.1.3.1 Efficiency Gains and Time Benefits

Efficiency was mentioned as a primary driver for AI adoption [E1, E2, E4, E5, E7, E9, E11]. AI is anticipated to generate scouting reports and videos, identify specific player profiles, and complete tasks in minutes that currently take weeks [E4, E9, E11]. It acts as a 'personal assistant' by rapidly aggregating and correlating diverse data sources for decision-making [E4]. AI presents a key opportunity to synthesize disparate information sources into coherent and actionable insights [E4, E7, E8, E9].

4.1.3.2 Broader Scouting Coverage and Advanced Predictive Models

AI enables clubs to achieve more comprehensive and extensive scouting coverage [E2, E3, E5, E6, E8]. Clubs could track and evaluate almost any player in any professional league worldwide, reducing travel costs and facilitating clubs' market reach, especially valuable for smaller clubs with limited scouting personnel [E2, E5, E6].

Considerable potential exists for AI tools to analyze players' characters by integrating publicly accessible information, private social media data, and objective match data [E7].

AI can detect complex patterns and build predictive models beyond conventional analyses [E1, E2, E5, E6, E7, E10]. Ongoing work was mentioned to advance further models like VAEP (Valuing Actions by Estimating Probabilities) to assess the contribution of players' on-ball actions and xG [E1, E2]. Advancements in computer vision were expected to optimize further off-ball events like body pose estimation [E10].

4.1.3.3 More Strategic and Data-Backed Decision-Making

Integrating AI was seen as facilitating more strategic and robust data-backed decision-making, reducing bias, and eliminating the emotional component [E1, E4, E6, E7]. LLMs were perceived as an emerging opportunity [E3, E7, E8]. [E8] considered integrating LLMs with scouting databases and reports the industry's 'next big step.' By translating complex data into easily understandable text or dashboards, LLMs enhance accessibility for stakeholders such as scouts, board members, and sporting directors, thereby facilitating faster decision-making [E3, E7]. When combined with event, tracking, and body composition data, LLMs can identify complex patterns valuable for scouting and training analyses [E3].

4.1.3.4 Improving Data Gathering

Advances in technology were expected to enhance data gathering, reduce costs, and broaden accessibility, thus fostering AI adoption [E6, E8, E10, E11]. In particular, tracking data will become more accurate and accessible as computer vision improves [E10]. AI's applicability was highlighted, extending beyond scouting to fan engagement, attendance prediction, and game security [E4, E7, E8, E11].

4.1.4 Limitations and Adoption Barriers

While potential benefits of AI were widely recognized, several barriers hinder broader and effective implementation across the industry.

4.1.4.1 Cultural Resistance and Skepticism

Cultural and organizational resistance represented a fundamental impediment to AI adoption [E10/E12]. Experts described football as inherently conservative, prioritizing traditional methods and personal networks over new technologies [E1, E3, E6, E8, E9, E10, E11]. Some noted that 'football is very delayed in terms of technology' compared to other industries [E1, E7, E8, E11], with skepticism from experienced personnel at higher levels accustomed to traditional methods [E1, E4, E9]. Decision-makers, including coaches and scouts, often perceive data and AI as a threat to established practices or even their jobs [E1, E3, E4, E8]. Scouts even wonder what a computer could tell them that they wouldn't already know about a player [E1]. Dismissed as black boxes, there is a need to fully understand AI outputs [E2] and prove effectiveness [E9].

Leadership buy-in and strategic alignment remain rare [E1, E3, E7, E9]. Experts stressed adoption requires top-down support from owners, executives, coaching and scouting staff, with integration across departments [E1, E3, E4, E5, E6, E7, E8, E11]. Correspondingly, the lack of top-down conviction and a cohesive data strategy within clubs remains the most significant barrier. Without this, even top talent and models add little value if teams remain soiled and AI is not adequately integrated into decision-making processes [E1, E3, E4, E5, E7, E8, E10, E11].

A short-term return on investment (ROI) focus also works against long-term data strategies. Clubs in high-stakes environments often favor proven methods over novel AI solutions [E1, E8, E9]. Immediate impact and short-term results justify high investments in players rather than developing analytics teams, which are usually seen as superfluous expenses [E3, E8, E9].
A club's withdrawal from its data-driven strategy was noted by one expert following media and fan pressure for immediate results [E8]. Accordingly, two experts cited fans as a source of resistance [E2, E8].

Experts also highlighted a skill gap in effectively leveraging AI tools, as football professionals often lack data literacy and vice versa [E1, E3, E4, E8]. However, some experts observed a gradual convergence [E1, E4].

4.1.4.2 Technical Limitations and Data Challenges

Beyond cultural hurdles, eleven of twelve experts [E11/E12] cited technical and data issues as additional barriers. Cost was a major factor, as data is expensive to collect and process, especially tracking data [E3, E4, E5, E6, E8, E10, E11]. Costs disproportionately affect smaller clubs. Investments in data scientists or external consultancies and data providers are often weighed against acquiring new players [E3, E5, E6, E8, E9, E11].

While football has extensive public data, it is insufficient for sophisticated models [E10]. Event data is widely available, but tracking data, which is essential for complete player impact assessment, remains scarce, costly, and hard to measure [E5, E6, E8, E10]. Experts further pointed to AI's difficulties in capturing intangible human factors like mentality, leadership, and adaptation to new environments [E1, E2, E4, E5, E6, E7, E9, E11], vital for holistic player assessment, however, impossible to measure and to integrate into current predictive models.

Finally, football's complexity and fluid nature were noted as less data-friendly than sports like baseball, and current AI still fails to capture football's entire context [E2, E3, E4, E6, E7, E8, E10].

4.1.5 Competitive Advantage and Disruption Potential

Technical and data availability are expected to improve rapidly. The consensus among experts suggested that AI can deliver substantial competitive advantages in scouting and beyond.

4.1.5.1 AI as a Source of Competitive Advantage

Experts agreed that AI will fundamentally transform scouting and talent identification. One expert stressed that AI will be leveraged but won't replace human and traditional methods. All experts agreed on AI's role complementing traditional methods [12E / 12E]. Consistent with Christensen's (1997) Disruption Theory of innovations initially targeting underserved markets. AI and data science were seen as strategic imperatives for competitiveness and success, with statements including, 'if clubs don't open up to data analyses, nowadays, you are dead. You cannot compete,' 'AI in recruitment is not an alternative,' and 'the clubs that don't use it (AI) will fail,' regardless of their respective definitions of success [E1, E4, E10].

Achieving this advantage requires strategic alignment, strong leadership buy-in, and interdisciplinary teams, as highlighted as a crucial differentiator [E1, E3, E4, E8]. The necessity for even more comprehensive technical knowledge is evidenced by coaches starting to have appropriate data scientists on their coaching staff, developing proprietary, customized AI models and databases. Several experts suggested developing internal club models, although not all are AI-based [E4, E5, E7, E8, E11, E12].

External consultancies were considered especially appropriate for smaller clubs lacking resources for internal development [E3]. However, external data providers often solely supply data without solving club-specific problems, and access to data alone does not guarantee meaningful insights [E10]. Several experts stressed that smaller clubs could gain disproportionate advantages, advocating for their realization as AI was seen to become table stakes fairly soon [E4, E5, E7, E8, E9, E10, E11]. However, cost remains a major barrier, especially for smaller clubs, as big clubs possess the resources to invest in talent and technology, enabling them to build significant data departments and better processes [E3, E6, E8, E11].

These requirements for strategic alignment and developing internal competencies reflect dynamic capabilities (Teece et al, 1997; Barreto, 2010) as firms must integrate, build, and reconfigure internal and external competencies.

4.1.5.2 Sustainability AI-based Advantages

The sustainability of AI-based advantages is a critical consideration. Experts agreed that as AI and data-driven approaches become widely adopted and commoditized, the initial competitive edge held by early adopters is likely to be diminished or neutralized, given that most clubs use the same data and technology [E1, E5, E7, E8, E9, E10].

However, the consensus was that advantages will not disappear entirely, instead, the nature of competition will evolve. Several experts suggested that the advantage won't diminish as no two clubs will use the same models. Competition will be centered on differentiation through unique parameters and proprietary models rather than raw technological advantage [E1, E4, E12]. Early adopters' greater familiarity and experience with the technology will provide an advantage in '9 of 10 situations,' making it 'almost impossible' for late adopters to reach the same level quickly [E11]. Other experts suggested shifting AI applications toward enhancing match-day performance and winning games [E1, E5].

Overall, AI offers greater benefits to smaller clubs, with competitive advantage arising from developing distinctive models and parameters, a concept aligned with Blue Ocean Strategy's focus on value innovation (Kim & Mauborgne, 2005). This underscores the importance for clubs to rapidly develop AI capabilities to create and maintain a competitive edge.

4.2 Consumer Insights Survey

The literature and experts identified fan acceptance as a key driver in adopting AI technologies in football (Plattfaut & Koch, 2021). The consumer survey with n = 106 participants assessed perceptions of AI in football scouting and performance analytics for validation. The survey's outline can be found in Appendix II.

4.2.1 Demographics

This Section explores the demographic composition of our survey respondents after cleaning the data set for invalid respondents. This foundation provides a better understanding of the surveyed sample and indicates its reliability.

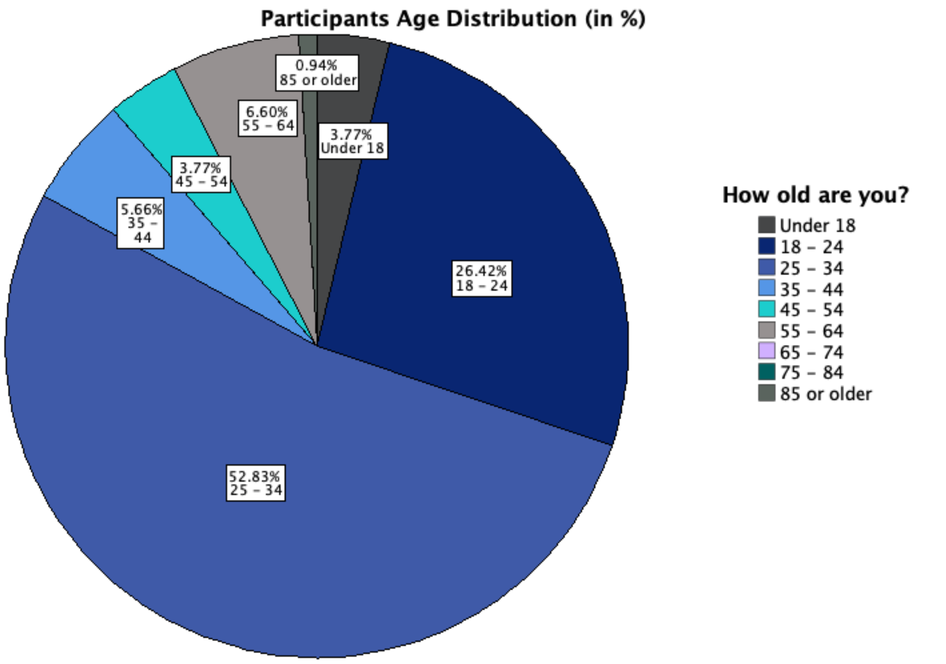

Figure 3: Answer Distribution of Question 1

The age distribution of respondents was uneven, with nearly 80% belonging to the two largest age groups. The most represented group was 25 – 34 years old (52.83%), followed by 18 – 24 years old (26.42%).

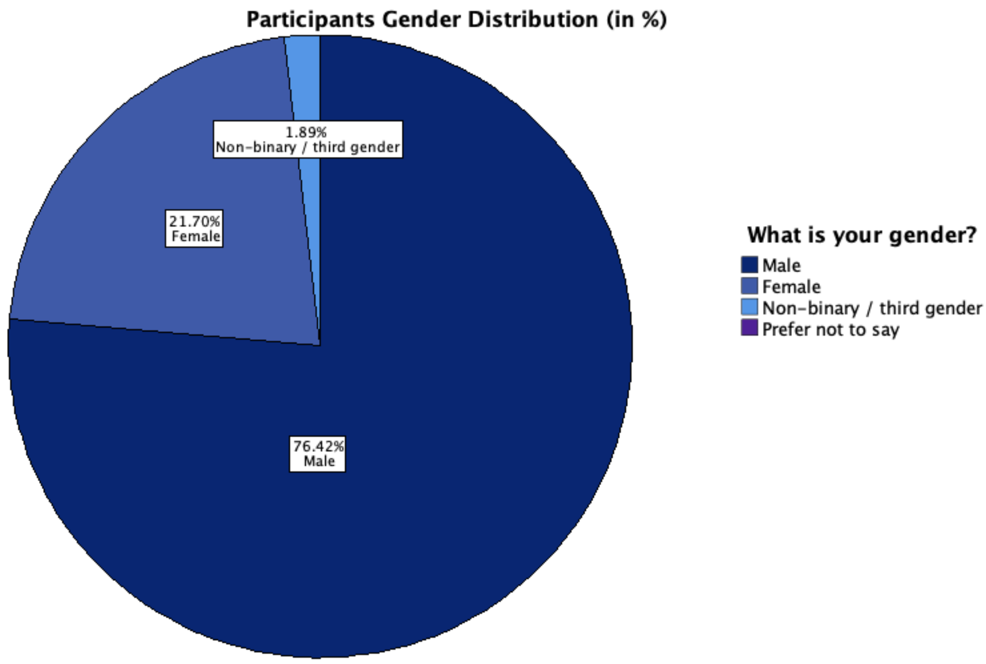

Figure 4: Answer Distribution of Question 2

The second question assessed gender, with 76.42% of respondents being male.

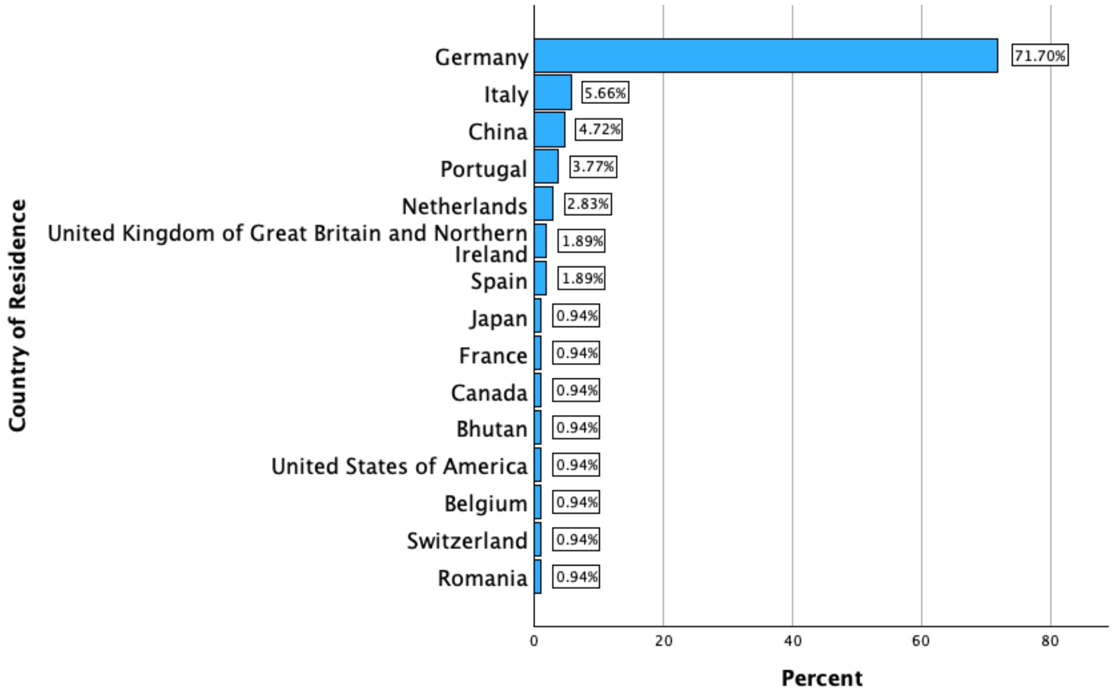

Figure 5: Answer Distribution of Question 3

The distribution of respondents' countries of residence was notably skewed, with 71.7% indicating Germany as their country of residence.

The demographic data indicated a predominantly male sample aged 25 to 34 years, primarily from Germany.

4.2.2 Football Engagement and Technological Awareness in Football

The survey targeted football fans by inquiring about their level of engagement with professional football, ensuring the sample reflected relevant perceptions.

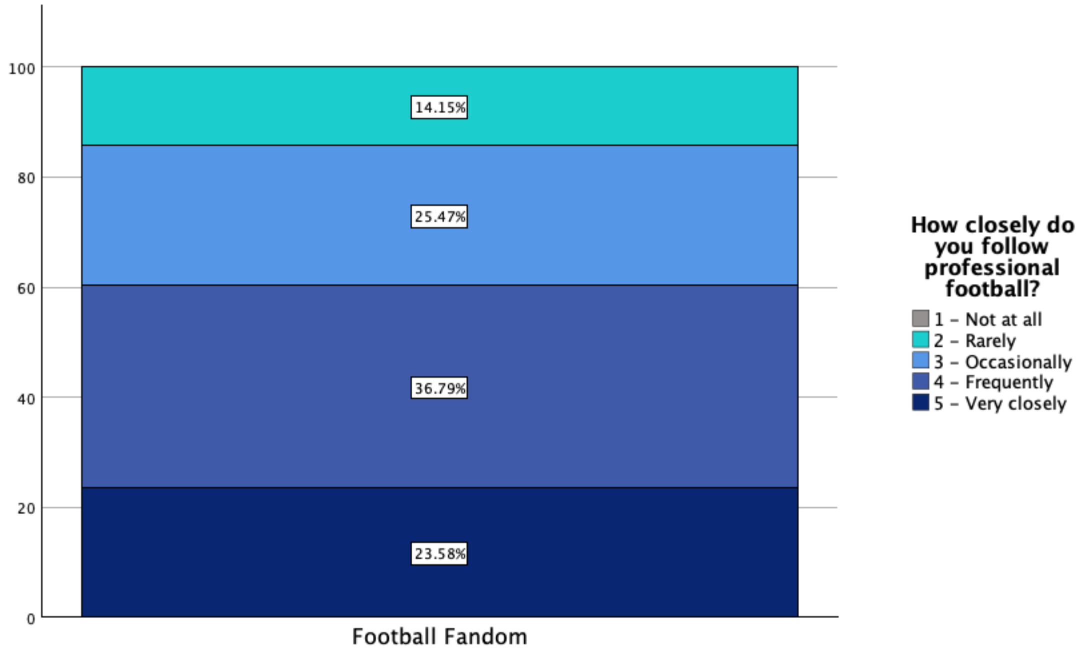

Figure 6: Answer Distribution of Question 4

Respondents who did not follow football were excluded from the analyses. Among the remaining participants, 85.78% reported at least occasionally following football, while 60.37% followed it frequently or very closely. This indicated a predominantly football-engaged respondent group.

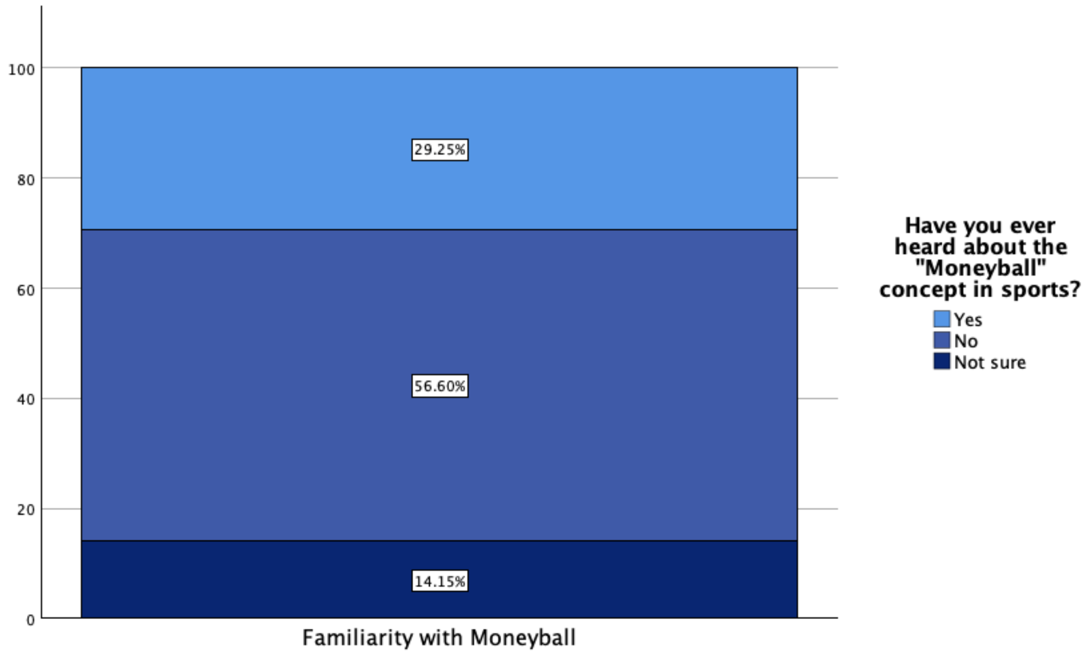

Figure 7: Answer Distribution of Question 5

Question five explored respondents' general familiarity with data science in sports by asking about their familiarity with Moneyball, which is regarded as revolutionary breakthrough in the field. Only 29.25% were sure of knowing the MA.

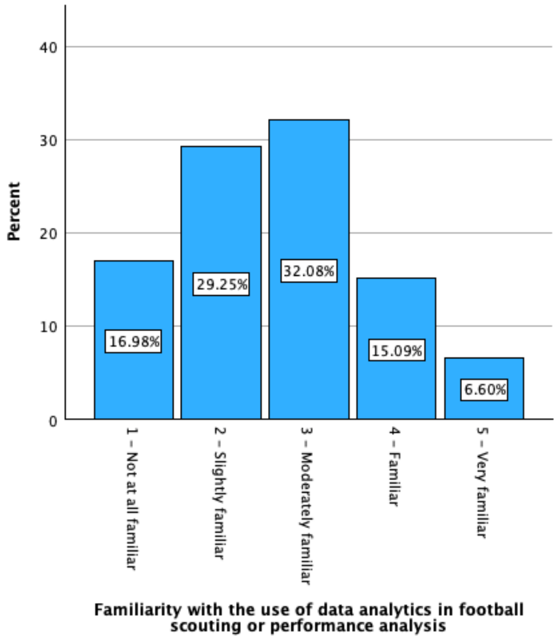

Figure 8: Answer Distribution of Question 6_1

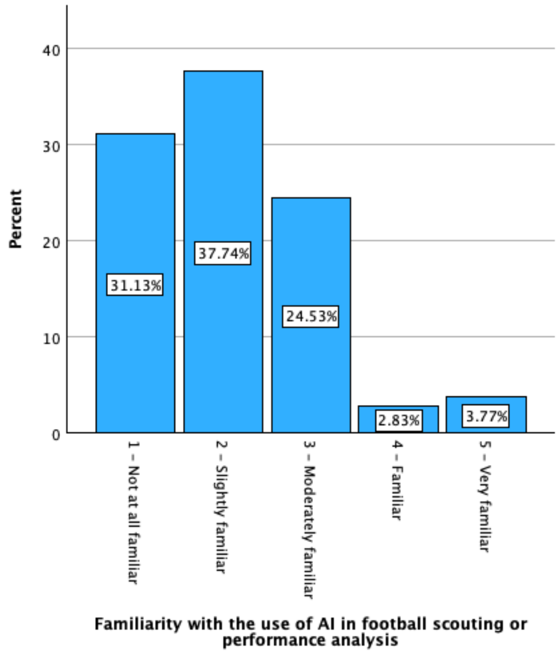

Figure 9: Answer Distribution of Question 6_2

Questions 6_1 and 6_2 assessed more particularly familiarity with data science and AI in football scouting and performance analysis. Approximately 22% of respondents reported being familiar or very familiar with data science, with only about 7% reporting familiarity with AI in this context.

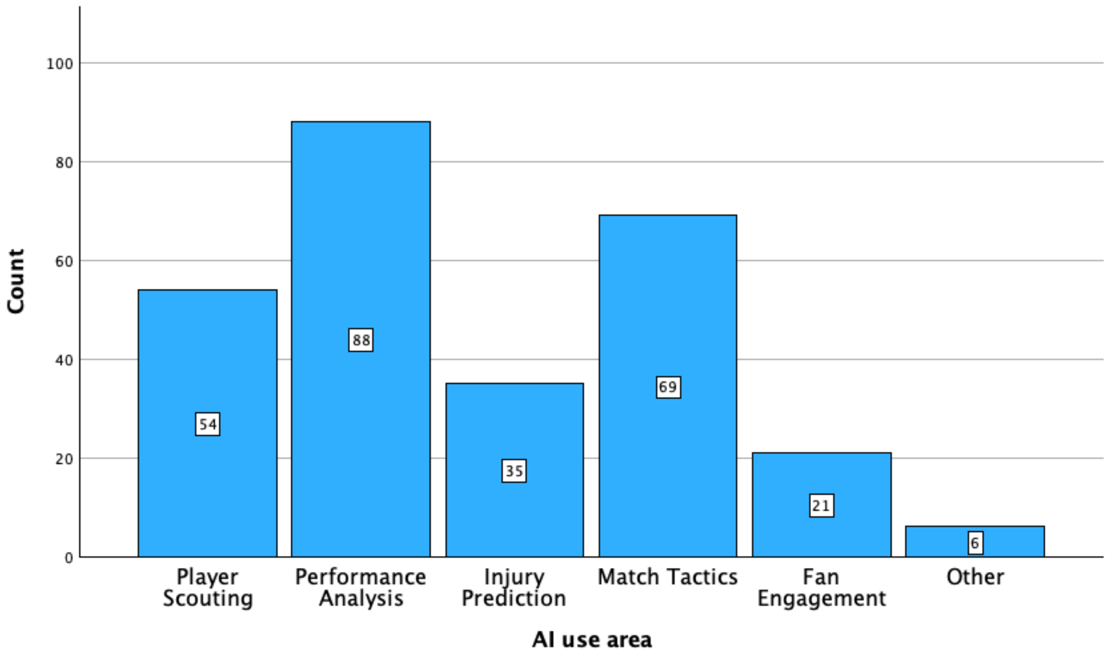

Figure 10: Answer Distribution of Question 7

Additionally, respondents identified performance analyses, match tactics, and player scouting as the most suitable application areas for AI, with question seven permitting multiple selections.

4.2.3 Descriptive Insights on AI Acceptance

For contextualization purposes, respondents' acceptance of AI in scouting was aggregated into three groups: Low (1.00 – 2.49), Neutral (2.50 – 3.99), and High (4.00 – 5.00). Most respondents (56.6%) were neutral, indicating an ambivalent attitude, while 25.5% showed high acceptance and 17.9% low acceptance. This distribution suggested a generally cautious yet open attitude towards AI, with many remaining undecided or skeptical.

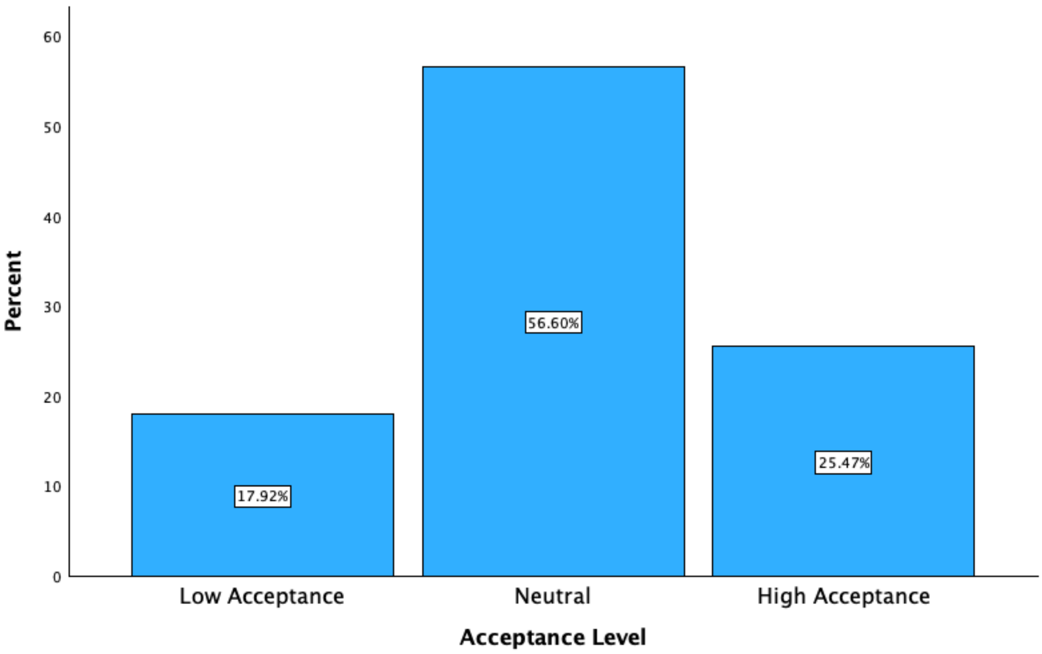

Figure 11: Distribution of Acceptance Level

4.2.4 Predictors of Fan Acceptance – Regression Based on TAM3

A hierarchical linear regression based on an extended TAM3 model was conducted to identify key drivers of participants' acceptance of AI-based scouting. The dependent variable was the aggregated variable 'Acceptance.' All aggregated variables were tested, ensuring internal consistency (Cronbach's alpha > 0.7). Given the aggregated variables' approximate continuous distribution, linear regression was deemed appropriate over ordinal regression.

Model 1 included the core TAM3-related and theoretical predictors: **Perceived Usefulness (PU), AI Trust, Authenticity Loss (Authenticity), Cultural Resistance,** and **Football Involvement**. Collectively, these variables explained a substantial portion of the variance in acceptance (Adjusted $R^2 = 0.608$), and the model was statistically significant ($F(5,100) = 33.635$, $p < 0.001$).

All five predictors in Model 1 were statistically significant at the 5% level:

> **AI Trust** showed the strongest standardized effect ($\beta = 0.271$, $p = 0.003$), indicating that higher trust in AI significantly predicts greater acceptance.
>
> **Perceived Usefulness (PU)** was also a strong predictor ($\beta = 0.224$, $p = 0.009$), suggesting that participants who recognize the utility of AI in scouting are more likely to accept its implementation.
>
> Both **Authenticity** ($\beta = -0.209$, $p = 0.045$) and **Cultural Resistance** ($\beta = -0.265$, $p = 0.013$) were negatively associated with acceptance, indicating that concerns about AI diminishing football's authenticity or disrupting its cultural norms reduce acceptance.
>
> **Football Involvement** also emerged as a significant positive predictor ($\beta = 0.147$, $p = 0.024$), suggesting that participants more engaged with the sport are slightly more open to technological innovation in this context.

Model 2 added gender dummy variables, Model 3 introduced age group dummies, and Model 4 included Moneyball awareness. None of these predictors reached statistical significance, with only a minor increase in explained variance (increase in Adjusted R^2 from 0.608 to 0.622).

Model 1's strong explanatory power and the significance of additional predictors indicate that the core TAM3 constructs are the key determinants of AI acceptance in football scouting. The results emphasized the importance of trust in AI and perceived usefulness, while emotional and cultural resistance remain barriers.

Table 2 - TAM Regression Model Summary – Acceptance

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.792[a]	.627	.608	.54308	.627	33.635	5	100	<.001
2	.804[b]	.647	.621	.53401	.020	2.712	2	98	.071
3	.807[c]	.651	.618	.53659	.004	.531	2	96	.590
4	.813[d]	.661	.622	.53371	.011	1.519	2	94	.224

a. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes

b. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes, Dummy: Male, Dummy: Nonbinary

c. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes, Dummy: Male, Dummy: Nonbinary, Dummy: Age young adults, Dummy: Age youth

d. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes, Dummy: Male, Dummy: Nonbinary, Dummy: Age young adults, Dummy: Age youth, Dummy: Moneyball yes, Dummy: Moneyball no

e. Dependent Variable: Acceptance

Table 3 - TAM Regression Coefficients Table – Acceptance

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.289	.472		4.847	<.001		
	PU	.243	.091	.224	2.674	.009	.530	1.887
	AITrust	.291	.095	.271	3.081	.003	.481	2.079
	Authenticity	-.169	.083	-.209	-2.026	.045	.349	2.862
	CulturalRes	-.216	.085	-.265	-2.534	.013	.341	2.931
	Football Involvment	.129	.056	.147	2.296	.024	.915	1.092
2	(Constant)	2.492	.482		5.167	<.001		
	PU	.233	.089	.215	2.602	.011	.528	1.893
	AITrust	.262	.094	.244	2.791	.006	.471	2.125
	Authenticity	-.210	.085	-.261	-2.469	.015	.323	3.099
	CulturalRes	-.189	.085	-.232	-2.228	.028	.333	3.007
	Football Involvment	.124	.056	.141	2.200	.030	.878	1.139
	Dummy: Male	.004	.132	.002	.033	.973	.859	1.164
	Dummy: Nonbinary	-.920	.413	-.145	-2.228	.028	.852	1.173
3	(Constant)	2.383	.508		4.696	<.001		
	PU	.221	.091	.204	2.431	.017	.518	1.931
	AITrust	.266	.095	.248	2.814	.006	.469	2.132
	Authenticity	-.200	.089	-.248	-2.255	.026	.300	3.328
	CulturalRes	-.196	.088	-.240	-2.220	.029	.311	3.217
	Football Involvment	.123	.057	.140	2.165	.033	.872	1.146
	Dummy: Male	.021	.136	.010	.154	.878	.811	1.234
	Dummy: Nonbinary	-.866	.421	-.136	-2.057	.042	.827	1.209
	Dummy: Age youth	.113	.167	.060	.675	.501	.464	2.154
	Dummy: Age young adults	.154	.150	.089	1.030	.305	.486	2.057
4	(Constant)	2.357	.514		4.582	<.001		
	PU	.193	.092	.179	2.106	.038	.501	1.997
	AITrust	.287	.095	.268	3.017	.003	.458	2.183
	Authenticity	-.183	.090	-.227	-2.040	.044	.291	3.436
	CulturalRes	-.211	.088	-.259	-2.389	.019	.307	3.262
	Football Involvment	.109	.057	.125	1.917	.058	.854	1.172
	Dummy: Male	.018	.136	.009	.131	.896	.807	1.239
	Dummy: Nonbinary	-.892	.420	-.141	-2.122	.036	.821	1.218
	Dummy: Age youth	.145	.167	.077	.870	.386	.458	2.181
	Dummy: Age young adults	.196	.151	.113	1.300	.197	.473	2.114
	Dummy: Moneyball yes	.212	.170	.111	1.242	.217	.447	2.235
	Dummy: Moneyball no	.006	.157	.003	.036	.971	.446	2.243

a. Dependent Variable: Acceptance

Before regression analyses, the underlying assumptions of multiple linear regression were tested. The normality of residuals, linearity between predictors and the dependent variable, and homoscedasticity were visually assessed and reasonably satisfied. Multicollinearity was ruled out as all Variance Inflation Factor (VIF) were not substantially higher than 3. These checks confirm that the assumptions for applying linear regression were reasonably met. All assumptions were tested accordingly prior every regression analyses.

4.2.5 Predictors of Disruption Potential – Regression Based on TAM3

To explore the factors influencing perceptions of AI-based scouting's disruptive potential in football, a hierarchical linear regression was conducted using the extended TAM3 framework. Disruption Potential was the dependent variable, with aggregated predictors validated via Cronbach's alpha (>0.7), supporting their use in the analyses.

Model 1 included the core set of theoretically driven predictors: Perceived Usefulness (PU), AI Trust, Authenticity Loss (Authenticity), Cultural Resistance, and Football Involvement. The model was statistically significant ($F(5, 100) = 12.466$, $p < 0.001$) and explained a meaningful share of the variance in disruption potential (Adjusted $R^2 = 0.353$).

Perceived Usefulness (PU) and AI Trust were the only statistically significant predictors at the 5% level:

> **Perceived Usefulness (PU)** exhibited the strongest positive effect ($\beta = 0.366$, $p < 0.001$), suggesting that individuals who see AI as beneficial are more likely to consider it a disruptive edge in football scouting.
>
> **AI Trust** was also a significant positive driver ($\beta = 0.295$, $p = 0.011$), supporting the idea that trust in AI systems enhances perceptions of their ability to transform the industry significantly.
>
> **Football Involvement** showed a negative association with disruption potential ($\beta = -0.161$, $p = 0.052$), which marginally misses the 5% significance threshold but may indicate that more involved fans are more skeptical of AI's potential to transform football scouting.
>
> **Authenticity** ($\beta = 0.192$, $p = 0.152$) and **Cultural Resistance** ($\beta = -0.132$, $p = 0.327$) were not statistically significant predictors in this model.

Subsequent models added demographic and contextual variables. Model 2 introduced gender, Model 3 added age groups, and Model 4 included Moneyball awareness. None of which were statistically significant, with minimal change in explained variance.

Thus, Model 1 remained the most explanatory. The findings highlighted perceived usefulness and trust in AI as key psychological factors influencing perceptions of AI as disruptive. In contrast, emotional and cultural dimensions, while relevant to acceptance, appeared less influential in shaping perceptions of disruption.

Table 4 - TAM Regression Model Summary – Disruption Potential

Model Summary[e]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.620[a]	.384	.353	.69396	.384	12.466	5	100	<.001
2	.627[b]	.393	.349	.69606	.009	.698	2	98	.500
3	.637[c]	.405	.350	.69584	.013	1.031	2	96	.361
4	.644[d]	.415	.347	.69747	.010	.776	2	94	.463

a. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes

b. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes, Dummy: Male, Dummy: Nonbinary

c. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes, Dummy: Male, Dummy: Nonbinary, Dummy: Age young adults, Dummy: Age youth

d. Predictors: (Constant), Football Involvment, PU, Authenticity, AITrust, CulturalRes, Dummy: Male, Dummy: Nonbinary, Dummy: Age young adults, Dummy: Age youth, Dummy: Moneyball yes, Dummy: Moneyball no

e. Dependent Variable: DisruptionPot

Table 5 - TAM Regression Coefficients Table – Disruption Potential

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1.618	.604		2.681	.009		
	PU	.394	.116	.366	3.391	<.001	.530	1.887
	AITrust	.315	.121	.295	2.607	.011	.481	2.079
	Authenticity	.153	.106	.192	1.443	.152	.349	2.862
	CulturalRes	-.107	.109	-.132	-.986	.327	.341	2.931
	Football Involvment	-.141	.072	-.161	-1.965	.052	.915	1.092
2	(Constant)	1.808	.629		2.876	.005		
	PU	.390	.117	.362	3.345	.001	.528	1.893
	AITrust	.294	.122	.275	2.398	.018	.471	2.125
	Authenticity	.118	.111	.147	1.061	.291	.323	3.099
	CulturalRes	-.087	.111	-.107	-.782	.436	.333	3.007
	Football Involvment	-.135	.073	-.155	-1.840	.069	.878	1.139
	Dummy: Male	-.099	.172	-.049	-.575	.566	.859	1.164
	Dummy: Nonbinary	-.620	.538	-.098	-1.151	.252	.852	1.173
3	(Constant)	1.528	.658		2.322	.022		
	PU	.380	.118	.352	3.223	.002	.518	1.931
	AITrust	.304	.123	.285	2.476	.015	.469	2.132
	Authenticity	.107	.115	.133	.928	.356	.300	3.328
	CulturalRes	-.070	.114	-.086	-.610	.544	.311	3.217
	Football Involvment	-.131	.074	-.150	-1.779	.078	.872	1.146
	Dummy: Male	-.042	.177	-.021	-.238	.812	.811	1.234
	Dummy: Nonbinary	-.485	.546	-.077	-.889	.376	.827	1.209
	Dummy: Age youth	.307	.216	.164	1.420	.159	.464	2.154
	Dummy: Age young adults	.217	.194	.126	1.115	.267	.486	2.057
4	(Constant)	1.570	.672		2.336	.022		
	PU	.352	.120	.327	2.935	.004	.501	1.997
	AITrust	.327	.124	.307	2.630	.010	.458	2.183
	Authenticity	.130	.117	.162	1.106	.271	.291	3.436
	CulturalRes	-.086	.115	-.107	-.748	.456	.307	3.262
	Football Involvment	-.145	.075	-.166	-1.939	.055	.854	1.172
	Dummy: Male	-.039	.178	-.019	-.221	.826	.807	1.239
	Dummy: Nonbinary	-.485	.549	-.077	-.883	.379	.821	1.218
	Dummy: Age youth	.335	.218	.179	1.538	.127	.458	2.181
	Dummy: Age young adults	.257	.197	.149	1.301	.197	.473	2.114
	Dummy: Moneyball yes	.101	.223	.054	.456	.650	.447	2.235
	Dummy: Moneyball no	-.099	.205	-.057	-.483	.630	.446	2.243

a. Dependent Variable: DisruptionPot

4.2.6 Predictors of AI Trust – Regression Based on TAM3

A hierarchical linear regression analysis was performed to identify factors influencing trust in AI-based scouting systems, with the aggregated AI Trust variable as the dependent variable. All constructs demonstrated good internal consistency (Cronbach's alpha > 0.7), confirming their reliability and justifying the use of linear regression given the continuous nature of the dependent variable.

Model 1 included the five theoretical predictors: Perceived Usefulness (PU), Authenticity Loss (Authenticity), Cultural Resistance, and Football Involvement. It explained a considerable amount of the variance in AI Trust (Adjusted $R^2 = 0.500$) and was statistically significant ($F(4,101) = 27.236$, $p < 0.001$).

Notably, only Perceived Usefulness (PU) demonstrated a statistically significant effect at the 5% level:

> **PU** had the strongest standardized coefficient (β = 0.590, $p < 0.001$), indicating that perceiving AI as useful in football scouting strongly increases participants' trust in such systems.

None of the extended models significantly improved explained variance or showed a notable effect on AI Trust. Specifically, adding dummy variables for gender (Model 2), age (Model 3), or Moneyball awareness (Model 4) did not yield statistically significant results. Consequently, Model 1 remained the most robust, highlighting perceived usefulness (PU) as the primary predictor of AI Trust. Demographic factors, emotional and cultural attitudes, football involvement, and familiarity with data science in sports did not significantly influence trust.

Table 6 - TAM Regression Model Summary – AI Trust

Model Summary[e]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.720[a]	.519	.500	.57180	.519	27.236	4	101	<.001
2	.728[b]	.529	.501	.57127	.010	1.094	2	99	.339
3	.729[c]	.531	.492	.57619	.002	.158	2	97	.854
4	.736[d]	.542	.494	.57527	.011	1.154	2	95	.320

a. Predictors: (Constant), Football Involvment, PU, Authenticity, CulturalRes

b. Predictors: (Constant), Football Involvment, PU, Authenticity, CulturalRes, Dummy: Nonbinary, Dummy: Male

c. Predictors: (Constant), Football Involvment, PU, Authenticity, CulturalRes, Dummy: Nonbinary, Dummy: Male, Dummy: Age young adults, Dummy: Age youth

d. Predictors: (Constant), Football Involvment, PU, Authenticity, CulturalRes, Dummy: Nonbinary, Dummy: Male, Dummy: Age young adults, Dummy: Age youth, Dummy: Moneyball no, Dummy: Moneyball yes

e. Dependent Variable: AITrust

Table 7 - TAM Regression Coefficients Table – AI Trust

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1.987	.456		4.353	<.001		
	PU	.595	.075	.590	7.922	<.001	.859	1.164
	Authenticity	-.130	.087	-.173	-1.496	.138	.357	2.800
	CulturalRes	-.067	.090	-.088	-.747	.457	.343	2.915
	Football Involvment	-.069	.059	-.084	-1.168	.246	.928	1.078
2	(Constant)	2.132	.469		4.543	<.001		
	PU	.578	.076	.573	7.600	<.001	.836	1.196
	Authenticity	-.162	.090	-.217	-1.813	.073	.333	3.000
	CulturalRes	-.044	.091	-.058	-.488	.626	.333	3.000
	Football Involvment	-.062	.060	-.076	-1.041	.300	.888	1.126
	Dummy: Male	-.087	.141	-.046	-.620	.537	.863	1.159
	Dummy: Nonbinary	-.639	.437	-.108	-1.461	.147	.871	1.148
3	(Constant)	2.216	.496		4.464	<.001		
	PU	.579	.078	.574	7.442	<.001	.814	1.229
	Authenticity	-.157	.094	-.209	-1.673	.098	.309	3.235
	CulturalRes	-.051	.095	-.067	-.538	.592	.312	3.207
	Football Involvment	-.064	.061	-.078	-1.051	.296	.882	1.133
	Dummy: Male	-.106	.146	-.056	-.725	.470	.815	1.227
	Dummy: Nonbinary	-.680	.447	-.115	-1.521	.131	.847	1.180
	Dummy: Age youth	-.100	.179	-.057	-.562	.576	.466	2.147
	Dummy: Age young adults	-.064	.161	-.039	-.396	.693	.487	2.053
4	(Constant)	2.095	.511		4.099	<.001		
	PU	.592	.078	.586	7.561	<.001	.802	1.247
	Authenticity	-.178	.095	-.237	-1.875	.064	.302	3.314
	CulturalRes	-.033	.095	-.043	-.346	.730	.307	3.258
	Football Involvment	-.049	.061	-.060	-.797	.428	.859	1.164
	Dummy: Male	-.109	.146	-.057	-.743	.459	.812	1.231
	Dummy: Nonbinary	-.674	.448	-.114	-1.506	.135	.841	1.189
	Dummy: Age youth	-.124	.179	-.071	-.690	.492	.461	2.170
	Dummy: Age young adults	-.100	.162	-.062	-.617	.539	.475	2.106
	Dummy: Moneyball yes	-.054	.184	-.030	-.292	.771	.448	2.233
	Dummy: Moneyball no	.138	.168	.085	.822	.413	.449	2.227

a. Dependent Variable: AITrust

4.2.7 Mediator & Moderator Analysis

To further explore the psychological mechanisms underlying participants' acceptance of AI-based scouting systems, mediator and moderator analyses were conducted using PROCESS V 5.0 (Hayes, 2022).

4.2.7.1 PU as Mediator between Football Involvement and Acceptance

The first analysis tested whether PU mediates the relationship between Football Involvement and Acceptance using PROCESS Model 4.

The analyses revealed that Football Involvement did not significantly predict Perceived Usefulness (PU) ($p = 0.668$), indicating that greater football engagement did not enhance perceptions of AI's usefulness. In contrast, PU significantly predicted Acceptance ($B = 0.62$, $p < 0.001$), affirming its role as a key determinant of AI acceptance. Although Football

Involvement had a significant direct effect on Acceptance (p = 0.005), the indirect effect via PU was not significant, as the 95% bootstrap confidence interval included zero. Thus, PU does not mediate the relationship between Football Involvement and Acceptance. These findings suggested that the link between Football Involvement and Acceptance is not mediated by PU, aligning with prior evidence that PU influences Acceptance independently of football engagement.

Table 8 - PU as Mediator between Football Involvement and Acceptance

```
  Model: 4
      Y: Accept
      X: Q4
      M: PU

Sample
Size:  106

**************************************************************************

OUTCOME VARIABLE:
 PU

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .0422      .0018      .6471      .1853     1.0000   104.0000      .6677

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.4442      .3043    11.3196      .0000     2.8408     4.0476
Q4           -.0342      .0795     -.4305      .6677     -.1919      .1235

**************************************************************************

OUTCOME VARIABLE:
 Accept

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6082      .3699      .4839    30.2298     2.0000   103.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .5202      .3931     1.3233      .1887     -.2594     1.2998
Q4            .1997      .0688     2.9022      .0045      .0632      .3362
PU            .6215      .0848     7.3296      .0000      .4533      .7897

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y ******************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .1997      .0688     2.9022      .0045      .0632      .3362

Indirect effect(s) of X on Y:
       Effect     BootSE   BootLLCI   BootULCI
PU     -.0213      .0538     -.1326      .0816

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

4.2.7.2 AI Trust as Mediator between Authenticity Loss and Acceptance

To investigate whether AI Trust mediates the relationship between concerns about authenticity loss in football and acceptance of AI-based scouting, another mediator analysis was conducted using PROCESS Model 4.

Results showed that perceived authenticity loss negatively predicted AI Trust (B = -0.327, $p < 0.001$), indicating that authenticity concerns diminish trust in AI systems. AI Trust, in turn, positively predicted Acceptance (B = 0.447, $p < 0.001$). The indirect effect of authenticity concerns on acceptance via AI Trust was significant (indirect effect = -0.146, 95% CI [-0.236, -0.069]), confirming mediator. Authenticity also had a significant direct negative effect on acceptance (B = -0.364, $p < 0.001$), suggesting partial mediator.

Overall, concerns about authenticity influence fan acceptance both directly and through their impact on trust in AI-based technologies.

Table 9 - AI Trust as Mediator between Authenticity and Acceptance

```
  Model: 4
      Y: Accept
      X: Authenti
      M: AITrust

Sample
Size:  106

**************************************************************************
OUTCOME VARIABLE:
 AITrust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4353      .1895      .5350    24.3118     1.0000   104.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.1093      .2142    19.1889      .0000     3.6847     4.5340
Authenti     -.3266      .0662    -4.9307      .0000     -.4579     -.1952

**************************************************************************
OUTCOME VARIABLE:
 Accept

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7354      .5409      .3526    60.6703     2.0000   103.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0397      .3705     8.2053      .0000     2.3050     3.7744
Authenti     -.3638      .0597    -6.0912      .0000     -.4822     -.2453
AITrust       .4467      .0796     5.6116      .0000      .2888      .6046

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.3638      .0597    -6.0912      .0000     -.4822     -.2453

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
AITrust     -.1459      .0425     -.2357     -.0692

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

4.2.7.3 Acceptance as Mediator between PU and Disruption Potential

This mediator analysis used PROCESS Model 4 to investigate whether Acceptance of AI mediated the relationship between PU and Disruption Potential in scouting.

Results showed that PU significantly predicted Acceptance ($B = 0.611$, $p < 0.001$, 95% CI [0.283, 0701]), indicating that higher perceived usefulness was associated with greater perceived disruption potential. However, Acceptance's effect on Disruption Potential was marginal ($B = 0.169$, $p = 0.087$), with a 95% CI including zero, suggesting limited statistical robustness. The indirect effect of PU on Disruption Potential via Acceptance was non-significant ($B = 0.103$, 95% CI [-0.019, 0.230]), indicating no mediator.

These findings suggested that perceived usefulness directly influenced perceptions of AI's disruptive potential, independent of Acceptance.

Table 10 - Acceptance as Mediator between PU and Disruption Potential

```
 Model: 4
     Y: DisrPot
     X: PU
     M: Accept

Sample
Size:  106

**************************************************************************

OUTCOME VARIABLE:
 Accept

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5642      .3183      .5184    48.5699     1.0000   104.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.2933      .2992     4.3223      .0000      .6999     1.8866
PU            .6111      .0877     6.9692      .0000      .4372      .7850

**************************************************************************

OUTCOME VARIABLE:
 DisrPot

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5699      .3248      .5124    24.7758     2.0000   103.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.3398      .3231     4.1468      .0001      .6990     1.9806
PU            .4919      .1056     4.6585      .0000      .2825      .7013
Accept        .1685      .0975     1.7287      .0869     -.0248      .3619

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .4919      .1056     4.6585      .0000      .2825      .7013

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
Accept      .1030      .0628     -.0185      .2303

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

4.2.7.4 AI Trust as Mediator between Cultural Resistance and Acceptance

This fourth mediator model examined whether AI Trust mediates the relationship between Cultural Resistance and Acceptance.

Results indicated that higher Cultural Resistance is significantly associated with lower AI Trust ($B = -0.308$, $p < 0.001$). Additionally, AI Trust positively predicts Acceptance ($B = 0.449$, $p < 0.001$). Both the direct effect of Cultural Resistance on Acceptance ($B = -0.392$, $p < 0.001$) and the indirect effect through AI Trust ($B = -0.138$, 95% CI [-0.232, -0.062]) were significant, indicating partial mediator.

These findings suggested that cultural resistance reduced acceptance of AI both directly and indirectly by diminishing trust, emphasizing the need to address emotional and cultural concerns to facilitate the integration of AI in football.

Table 11 - AI Trust as Mediator between Cultural Resistance and Acceptance

```
  Model: 4
      Y: Accept
      X: CultRes
      M: AITrust

Sample
Size:  106

**************************************************************************

OUTCOME VARIABLE:
 AITrust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4053      .1643      .5516    20.4446     1.0000   104.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.0301      .2152    18.7240      .0000     3.6033     4.4570
CultRes      -.3079      .0681    -4.5216      .0000     -.4429     -.1729

**************************************************************************

OUTCOME VARIABLE:
 Accept

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7539      .5683      .3315    67.8044     2.0000   103.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0901      .3488     8.8580      .0000     2.3983     3.7820
CultRes      -.3917      .0577    -6.7833      .0000     -.5062     -.2772
AITrust       .4488      .0760     5.9037      .0000      .2980      .5995

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.3917      .0577    -6.7833      .0000     -.5062     -.2772

Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
AITrust     -.1382      .0438     -.2316     -.0616

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

4.2.7.5 Football Involvement as Moderator between AI Trust and Acceptance

This analysis examined whether Football involvement moderates the relationship between AI Trust and Acceptance using PROCESS Model 1.

Results showed that AI Trust significantly predicted Acceptance ($B = 0.678$, $p < 0.001$), as did Football Involvement ($B = 0.220$, $p = 0.001$). However, the interaction between AI Trust and

Football Involvement was not statistically significant (B = 0.082, p = 0.262), with a minimal change in R^2 ($\Delta R^2 = 0.007$) and a confidence interval including zero.

These findings suggested that Football Involvement did not influence the strength of the relationship between AI Trust and Acceptance, which remains consistent across levels of football engagement.

Table 12 - Football Involvement as Moderator between AI Trust and Acceptance

```
  Model: 1
      Y: Accept
      X: AITrust
      W: Q4

Sample
Size:  106

**************************************************************************

OUTCOME VARIABLE:
 Accept

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6653      .4426      .4322    27.0008     3.0000   102.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.3252      .0640    51.9770      .0000     3.1983     3.4520
AITrust       .6777      .0796     8.5188      .0000      .5199      .8355
Q4            .2201      .0652     3.3743      .0010      .0907      .3495
Int_1         .0817      .0725     1.1280      .2620     -.0620      .2254

Product terms key:
 Int_1    :        AITrust  x        Q4

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0070     1.2725     1.0000   102.0000      .2620
----------
    Focal predict: AITrust  (X)
          Mod var: Q4       (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   AITrust    Q4         Accept     .
BEGIN DATA.
     -.7799     -.6981     2.6875
      .0535     -.6981     3.2047
      .8868     -.6981     3.7219
     -.7799      .3019     2.8438
      .0535      .3019     3.4292
      .8868      .3019     4.0145
     -.7799     1.3019     3.0002
      .0535     1.3019     3.6536
      .8868     1.3019     4.3071
END DATA.
GRAPH/SCATTERPLOT=
 AITrust  WITH     Accept   BY       Q4       .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

NOTE: The following variables were mean centered prior to analysis:
          Q4       AITrust
```

4.2.7.6 Football Involvement as Moderator between PU and AI Trust

This study examined whether Football Involvement moderates the relationship between PU and AI Trust using PROCESS Model 1.

PU significantly predicted AI Trust (B = 0.687, $p < 0.001$), indicating that higher perceived usefulness was associated with greater trust in AI-based scouting. The interaction between PU and Football Involvement was non-significant (B = 0.010, $p = 0.884$), with negligible change in explained variance ($\Delta R^2 < 0.001$). The 95% confidence interval for the interaction included zero (-0.128 to 0.148), suggesting that Football Involvement did not moderate the PU and AI Trust relationship.

Overall, the association between PU and trust remained consistent regardless of participants' level of football engagement.

Table 13 - Football Involvement as Moderator between PU and AI Trust

```
  Model: 1
      Y: AITrust
      X: PU
      W: Q4

Sample
Size:  106

**************************************************************************
OUTCOME VARIABLE:
 AITrust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6835      .4671      .3586    29.8038     3.0000   102.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.1135      .0582    53.4884      .0000     2.9981     3.2290
PU            .6868      .0730     9.4086      .0000      .5420      .8316
Q4           -.0322      .0593     -.5438      .5877     -.1497      .0853
Int_1         .0102      .0696      .1461      .8841     -.1278      .1482

Product terms key:
 Int_1    :        PU       x        Q4

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0001      .0214     1.0000   102.0000      .8841
----------
    Focal predict: PU       (X)
          Mod var: Q4       (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PU         Q4         AITrust    .
BEGIN DATA.
     -.6509     -.6981     2.6936
      .0157     -.6981     3.1467
      .6824     -.6981     3.5999
     -.6509      .3019     2.6547
      .0157      .3019     3.1147
      .6824      .3019     3.5746
     -.6509     1.3019     2.6159
      .0157     1.3019     3.0826
      .6824     1.3019     3.5493
END DATA.
GRAPH/SCATTERPLOT=
 PU       WITH     AITrust  BY       Q4       .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

NOTE: The following variables were mean centered prior to analysis:
          Q4       PU
```

4.2.7.7 Age as Moderator of the Indirect Effect of PU on Acceptance via AI Trust

To examine whether age moderated the indirect effect of PU on Acceptance through AI Trust, we used PROCESS Model 7.

PU significantly predicted AI Trust ($B = 0.684$, $p < 0.001$), indicating a positive association across all age groups. The interaction between PU and age was not significant ($B = 0.061$, $p = 0.277$), and the index of moderated mediator included zero (Index = 0.028, 95% CI [-0.004, 0.097]), suggesting no moderator by age. The conditional indirect effects were significant for both younger (Q1 = -1.05, B = 0.284) and older age groups (Q1 = 0.95, B = 0,399), with confidence intervals excluding zero.

Overall, the mediating role of AI Trust in the PU-Acceptance relationship appeared consistent across age groups.

Table 14 - Age as Moderator of the Indirect Effect of PU on Acceptance via AI Trust (1)

```
  Model: 7
      Y: Accept
      X: PU
      M: AITrust
      W: Q1

Sample
Size:  106

**************************************************************************

OUTCOME VARIABLE:
 AITrust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6878      .4730      .3546    30.5170     3.0000   102.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.1164      .0579    53.8093      .0000     3.0015     3.2313
PU            .6842      .0728     9.3925      .0000      .5397      .8287
Q1            .0446      .0501      .8900      .3756     -.0548      .1441
Int_1         .0606      .0554     1.0930      .2770     -.0494      .1706

Product terms key:
 Int_1    :        PU       x        Q1

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0062     1.1947     1.0000   102.0000      .2770
----------
    Focal predict: PU       (X)
          Mod var: Q1       (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   PU         Q1         AITrust    .
BEGIN DATA.
     -.6509    -1.0472     2.6656
      .0157    -1.0472     3.0794
      .6824    -1.0472     3.4933
     -.6509     -.0472     2.6708
      .0157     -.0472     3.1250
      .6824     -.0472     3.5793
     -.6509      .9528     2.6759
      .0157      .9528     3.1706
      .6824      .9528     3.6652
END DATA.
GRAPH/SCATTERPLOT=
 PU       WITH     AITrust  BY       Q1       .

**************************************************************************
```

Table 15 - Age as Moderator of the Indirect Effect of PU on Acceptance via AI Trust (2)

```
OUTCOME VARIABLE:
 Accept

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6446      .4155      .4489    36.6031     2.0000   103.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.8964      .3504     5.4115      .0000     1.2014     2.5914
PU            .2962      .1116     2.6537      .0092      .0748      .5175
AITrust       .4575      .1106     4.1366      .0001      .2382      .6769

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .2962      .1116     2.6537      .0092      .0748      .5175

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 PU          ->    AITrust     ->    Accept

         Q1     Effect     BootSE   BootLLCI   BootULCI
    -1.0472      .2840      .0810      .1299      .4526
     -.0472      .3118      .0875      .1453      .4937
      .9528      .3395      .1006      .1596      .5556

      Index of moderated mediation:
        Index     BootSE   BootLLCI   BootULCI
Q1      .0277      .0263     -.0039      .0974

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          Q1       PU
```

4.2.7.8 Age as Moderator between AI Trust and Acceptance

The following analyses examined whether age moderates the relationship between AI Trust and AI acceptance in football scouting. Using PROCESS Model 1, the interaction between AI Trust and age was not statistically significant ($B = 0.094$, $p = 0.229$, 95% CI [-0.059, 0.247]), indicating that the association between AI Trust and Acceptance did not differ across age groups. Conversely, AI Trust had a significant direct effect on acceptance ($B = 0.640$, $p < 0.001$), suggesting that trust in AI was a strong predictor of acceptance regardless of age.

Overall, the results implied that the influence of AI Trust on Acceptance remained consistent across age groups.

Table 16 - Age as Moderator between AI Trust and Acceptance

```
  Model: 1
      Y: Accept
      X: AITrust
      W: Q1

Sample
Size:  106

**************************************************************************
OUTCOME VARIABLE:
 Accept

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6206      .3852      .4768    21.2986     3.0000   102.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.3207      .0671    49.5134      .0000     3.1876     3.4537
AITrust       .6396      .0847     7.5521      .0000      .4716      .8076
Q1          -.0009      .0561     -.0165      .9868     -.1122      .1104
Int_1        .0935      .0774     1.2089      .2295     -.0599      .2470

Product terms key:
 Int_1    :        AITrust  x        Q1

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0088     1.4614     1.0000   102.0000      .2295
----------
    Focal predict: AITrust  (X)
          Mod var: Q1       (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   AITrust    Q1         Accept     .
BEGIN DATA.
     -.7799    -1.0472     2.8992
      .0535    -1.0472     3.3506
      .8868    -1.0472     3.8020
     -.7799     -.0472     2.8253
      .0535     -.0472     3.3547
      .8868     -.0472     3.8840
     -.7799      .9528     2.7515
      .0535      .9528     3.3587
      .8868      .9528     3.9660
END DATA.
GRAPH/SCATTERPLOT=
 AITrust  WITH     Accept   BY       Q1       .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

NOTE: The following variables were mean centered prior to analysis:
          Q1       AITrust
```

4.2.7.9 Age as Moderator between Cultural Resistance and AI Trust

This analysis examined whether age moderated the relationship between Cultural Resistance and AI Trust using PROCESS Model 1.

Results showed a significant negative main effect of Cultural Resistance on AI Trust (B = -0.310, $p < 0.001$), indicating that perceiving AI as a threat to cultural integrity decreases trust. The interaction between Cultural Resistance and Age was not significant (B = -0.084, p = 0.232), with the confidence interval including zero, suggesting age did not influence this relationship.

Overall, Cultural Resistance negatively impacts AI Trust regardless of age.

Table 17 - Age as Moderator between Cultural Resistance and AI Trust

```
  Model: 1
      Y: AITrust
      X: CultRes
      W: Q1

Sample
Size:  106

**************************************************************************

OUTCOME VARIABLE:
 AITrust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4196      .1760      .5545     7.2641     3.0000   102.0000      .0002

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.1151      .0723    43.0603      .0000     2.9716     3.2586
CultRes      -.3104      .0683    -4.5437      .0000     -.4459     -.1749
Q1           -.0024      .0584     -.0408      .9675     -.1181      .1134
Int_1        -.0838      .0697    -1.2029      .2318     -.2221      .0544

Product terms key:
 Int_1    :        CultRes  x        Q1

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0117     1.4469     1.0000   102.0000      .2318
----------
    Focal predict: CultRes  (X)
          Mod var: Q1       (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   CultRes    Q1         AITrust    .
BEGIN DATA.
     -.9780    -1.0472     3.3354
      .0220    -1.0472     3.1127
     1.0220    -1.0472     2.8901
     -.9780     -.0472     3.4150
      .0220     -.0472     3.1085
     1.0220     -.0472     2.8021
     -.9780      .9528     3.4946
      .0220      .9528     3.1043
     1.0220      .9528     2.7140
END DATA.
GRAPH/SCATTERPLOT=
 CultRes  WITH     AITrust  BY       Q1       .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

NOTE: The following variables were mean centered prior to analysis:
          Q1       CultRes
```

4.2.7.10 Age as Moderator between Authenticity and AI Trust

Using PROCESS Model 1, this last moderator analysis examined whether age moderated the relationship between perceived authenticity loss and AI Trust.

A significant negative effect of Authenticity on AI Trust (B = -0.333) indicated that concerns about reduced authenticity decrease trust. However, the interaction between authenticity loss and age was not significant (B = 0.009, p = 0.852), with the confidence interval including zero (95% CI [-0.086, 0.104]), suggesting no moderating role of age.

In Summary, authenticity negatively impacted trust in AI, regardless of age.

Table 18 - Age as Moderator between Authenticity and AI Trust

```
  Model: 1
      Y: AITrust
      X: Authenti
      W: Q1

Sample
Size:  106

**************************************************************************
OUTCOME VARIABLE:
 AITrust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4389      .1926      .5433     8.1110     3.0000   102.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.1147      .0720    43.2371      .0000     2.9718     3.2576
Authenti     -.3325      .0674    -4.9299      .0000     -.4663     -.1987
Q1           -.0323      .0593     -.5450      .5870     -.1500      .0854
Int_1         .0090      .0481      .1867      .8522     -.0864      .1043

Product terms key:
 Int_1    :        Authenti x        Q1

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0003      .0349     1.0000   102.0000      .8522
----------
    Focal predict: Authenti (X)
          Mod var: Q1       (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Authenti   Q1         AITrust    .
BEGIN DATA.
    -1.0503    -1.0472     3.5076
     -.0503    -1.0472     3.1658
     1.2830    -1.0472     2.7099
    -1.0503     -.0472     3.4659
     -.0503     -.0472     3.1330
     1.2830     -.0472     2.6891
    -1.0503      .9528     3.4241
     -.0503      .9528     3.1002
     1.2830      .9528     2.6683
END DATA.
GRAPH/SCATTERPLOT=
 Authenti WITH     AITrust  BY       Q1       .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

NOTE: The following variables were mean centered prior to analysis:
          Q1       Authenti
```

4.2.8 Single-Predictor Effects on AI Acceptance

To assess whether acceptance of AI in scouting differed across age groups, a one-way ANOVA was conducted. Given the categorical nature of the age variable and the aim to compare mean acceptance scores across multiple independent age groups, it was the appropriate method.

The analysis found no significant differences, $F(6, 99) = 1.164$, $p = 0.332$, indicating that acceptance levels did not systematically vary by age. Homogeneity of variances was confirmed by Levene's test, $p = 0.288$. The effect size was small ($\eta^2 = 0.066$), suggesting minimal practical differences despite some numerical variation.

Table 19 - Single-Predictor Effect of Age on Acceptance, one-way ANOVA

ANOVA

Accept

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.213	6	.869	1.164	.332
Within Groups	73.881	99	.746		
Total	79.094	105			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Accept	Eta-squared	.066	.000	.122
	Epsilon-squared	.009	-.061	.069
	Omega-squared Fixed-effect	.009	-.060	.069
	Omega-squared Random-effect	.002	-.010	.012

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Another one-way ANOVA assessed differences in acceptance by gender. Results indicated a significant effect of gender $F(2, 103) = 3.292$, $p = 0.041$, with at least one group differing. Homogeneity of variances was confirmed (Levene's test $p = 0.116$). However, the small non-binary sample (n=2) warrants caution. The effect size ($\eta^2 = 0.060$) was small to moderate. Descriptively males reported higher acceptance ($M = 3.40$) than females ($M = 3.14$), with non-binary participants reporting the lowest ($M = 2.00$). Due to the limited non-binary sample, further analysis was limited.

Table 20 - Single-Predictor Effect of Gender on Acceptance, one-way ANOVA

ANOVA

Accept

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.752	2	2.376	3.292	.041
Within Groups	74.343	103	.722		
Total	79.094	105			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	Upper
Accept	Eta-squared	.060	.000	.155
	Epsilon-squared	.042	-.019	.138
	Omega-squared Fixed-effect	.041	-.019	.137
	Omega-squared Random-effect	.021	-.010	.074

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Table 21 - Single-Predictor Effect of Gender on Acceptance, Descriptives

Descriptives

Accept

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound	Minimum	Maximum
Male	81	3.4033	.89399	.09933	3.2056	3.6010	1.00	5.00
Female	23	3.1449	.61813	.12889	2.8776	3.4122	1.67	4.00
Non-binary / third gender	2	2.0000	1.41421	1.00000	-10.7062	14.7062	1.00	3.00
Total	106	3.3208	.86792	.08430	3.1536	3.4879	1.00	5.00

A Pearson correlation analysis assessed the relationship between football involvement and acceptance of AI. This method was suitable for assessing linear associations between two continuous variables.

Results indicated a significant positive correlation ($r = 0.203$, $p = 0.037$), suggesting that higher engagement in football was associated with greater acceptance of AI technologies in scouting.

Table 22 - Single-Predictor Effect of Football Involvement on Acceptance, Pearson Correlation

Correlations

		FootInvo	Accept
FootInvo	Pearson Correlation	1	.203*
	Sig. (2-tailed)		.037
	N	106	106
Accept	Pearson Correlation	.203*	1
	Sig. (2-tailed)	.037	
	N	106	106

*. Correlation is significant at the 0.05 level (2-tailed).

Participants' awareness of the MA did not significantly influence their acceptance of AI in football scouting, as shown by a one-way ANOVA, $F(2, 103) = 1.088$, $p = 0.341$. Homogeneity of variances was confirmed (Levene's test $p = 0.804$). Although those aware of Moneyball reported higher acceptance ($M = 3.49$) than unaware ($M = 3.22$) or unsure ($M = 3.38$), these differences were not statistically significant. The effect size was small ($\eta^2 = 0.021$), indicating limited predictive power of Moneyball awareness on AI Acceptance.

Table 23 - Single-Predictor Effect of Moneyball Awareness on Acceptance, one-way ANOVA

ANOVA

Accept

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.636	2	.818	1.088	.341
Within Groups	77.458	103	.752		
Total	79.094	105			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Accept	Eta-squared	.021	.000	.089
	Epsilon-squared	.002	-.019	.071
	Omega-squared Fixed-effect	.002	-.019	.070
	Omega-squared Random-effect	.001	-.010	.036

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Table 24 - Single-Predictor Effect of Moneyball Awareness on Acceptance, Descriptives

Descriptives

Accept

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Yes	31	3.4946	.92645	.16639	3.1548	3.8344	1.33	5.00
No	60	3.2167	.86101	.11116	2.9942	3.4391	1.00	5.00
Not sure	15	3.3778	.75453	.19482	2.9599	3.7956	2.33	5.00
Total	106	3.3208	.86792	.08430	3.1536	3.4879	1.00	5.00

5 Conclusions

5.1 Main Findings – Triangulation

Literature, expert interviews, and survey data collectively suggested that AI was viewed as the next evolutionary step in football scouting, with the potential to improve decision-making and significantly disrupt industry practices. AI is expected to complement rather than replace human expertise. Sustainable competitive advantage will depend on strategic and effective integration of AI into organizational routines, proprietary data, and performance management systems.

The literature positions AI and ML as advancements in the ongoing data revolution in sports, transcending traditional principles and enabling more comprehensive analyses. Expert interviews supported this view, emphasizing that adopting AI and data science is a strategic necessity to create and maintain competitive advantage. Some suggest that failure to adopt these technologies may lead to obsolescence [E4, E10]. The consumer survey revealed limited familiarity with AI in football scouting among fans (approximately 7% familiarity), but also identified PU and trust in AI as key factors that predict acceptance and perceived disruptive potential. Once the effectiveness and credibility of AI are recognized, there is significant latent support for its application in performance analysis, tactical planning, and scouting, areas deemed accessible and relevant to fans. Although industry adoption remains nascent, the potential benefits of AI, when effectively communicated, align with expert opinions and public openness. Strategic initiatives such as proactive investment and clear value articulation are crucial for fostering AI integration in clubs.

AI significantly advances traditional scouting's limitations and mitigates subjectivity and cognitive biases (Andrews, 2022; Carey, 2024). Nonetheless, literature highlights the importance of XAI in bridging communication gaps between complex outputs and coaching staff, facilitating the translation of insights into actionable narratives (Carey, 2025; Rahimian et al., 2025). Experts universally view AI as an augmentation rather than a replacement, emphasizing its current limitations in assessing intangible factors such as leadership, mentality, and personality. While AI improves data analysis, reduces bias, and enhances efficiency, its optimal application in football relies on its synergistic integration with human expertise, particularly for qualitative judgments. Effective implementation strategies must focus on interdisciplinary teams and user-friendly outputs that support, rather than displace, experienced practitioners.

Cultural barriers and uncertainty impede the full integration of data-driven recruitment in football, primarily due to concerns about AI undermining human elements and traditions (Tuyls et al., 2021). Expert interviews revealed that cultural and organizational resistance are major obstacles, with the industry deemed lagging in technological progress and skeptical of AI and data, seen as threats to established practices and employment [E1, E3, E4, E8, E9]. Additional barriers included lack of leadership support, strategic misalignment, and external pressures from media and fans [E1, E3, E7, E8, E9]. Empirical data from surveys supported this, showing that cultural resistance negatively predicts AI acceptance ($\beta = -0.265$, $p = 0.013$). Consequently, overcoming deeply rooted traditionalism, fear, and mistrust necessitates a strategic approach to build trust, educate stakeholders, and secure top-level leadership to foster acceptance and reduce resistance within the football sector.

The literature indicated limited exploration of AI in scouting, with notable variability among clubs (Bate, 2025). Expert interviews revealed inconsistent perceptions of AI adoption, with some experts asserting widespread implementation and others indicating minimal use [E4, E5, E7, E8, E9, E11]. This pattern aligned with Rogers' Diffusion of Innovation model. Among fans, awareness of AI in football scouting is very low (7%), and general data science familiarity is modest (22%). Despite limited familiarity, acceptance levels are relatively high, with 56.6% neutral and 25.5% positive. The industry's AI adoption remains fragmented and cautious due to confidentiality and resource disparities. However, public receptiveness presents an opportunity for clubs to promote AI benefits and build trust, leveraging latent openness rather than assuming resistance based on current awareness levels.

Fan perception was recognized as a barrier to adoption in the literature (Plattfaut & Koch, 2021), though some experts support this view [E2, E8]. The consumer survey revealed that higher football involvement modestly predicts greater acceptance of AI ($r = 0.203$, $p = 0.037$). This involvement correlates negatively, albeit marginally, with perceptions of AI as disruptive, indicating that engaged fans were somewhat skeptical about AI transforming the sport. Despite concerns over authenticity and tradition, highly engaged fans are more receptive to AI when it is seen as an enhancer rather than a threat. Clubs should communicate transparently about AI's role in improving decision-making while preserving the sport's core human and cultural values, turning resistance into support among core fans.

5.1.1 Theoretical Implications

The conclusions of this study on AI's disruptive influence within football scouting and performance analytics offer implications for several management theories previously explored in the literature review. This research not only supports but also enhances existing theoretical frameworks by providing empirical evidence from a high-velocity, emotionally charged industry.

This study aligns with Rogers' Diffusion of Innovation Theory. The observation that AI adoption levels vary significantly across clubs, consistent with Rogers' categorization of adopters from innovators to laggards, highlights the reality of uneven technological diffusion within a single industry. The findings also indicated that fan acceptance is influenced by factors like football involvement and perceived usefulness, and that perceived authenticity loss decreases fans' acceptance level of AI. This suggested that for AI to attain widespread diffusion in football, clubs must strategically communicate its relative advantages and address perceived complexities to accelerate adoption beyond early innovators.

The research aligns with Christensen's Disruptive Innovation framework. The study identifies AI not as a technology intended for immediate displacement or disruption of traditional scouting, but rather as a complementary force that fundamentally transforms how scouting and talent identification operate. It addresses limitations within the complex football environment. Nevertheless, consistent with the initial trajectory of disruptive innovation, AI targets underserved needs and low-end segments. The experts' emphasis on AI as a strategic imperative and the perceived shift towards developing proprietary AI models for sustained competitive advantage indicate an evolutionary path wherein AI may challenge traditional sources of competitive advantage, rather than merely substitute them.

Future competitive advantage will likely derive from clubs measuring distinct metrics and developing unique parameters and proprietary models. This reflects the value of innovation concept of the Blue Ocean Strategy, creating uncontested market space. While AI adoption ultimately will become standard, true differentiation will come from leveraging AI to redefine player evaluation and scouting, enabling the creation of new opportunities where competition is irrelevant.

Finally, the study reinforces the Dynamic Capabilities framework. Experts highlight the necessity of strategic internal alignment, leadership support, and interdisciplinary teams in AI integration. AI is identified as an exogenous shock to the football industry, with technical barriers posing managerial challenges in opportunity sensing, timely decision-making, and market-oriented resource adaptation to remain competitive amidst ongoing disruption. It underscores the importance of a firm's ability to integrate, build, and reconfigure internal and external competencies.

5.1.2 Practical Implications

The insights derived from this study offer several practical implications for football clubs, governing bodies, and industry stakeholders striving to navigate the evolving landscape shaped by data analytics and AI.

Football organizations must adopt a strategy of integrated intelligence, synergizing AI-driven analytics with human expertise. Evidence indicates that AI functions as a powerful complement to, rather than a substitute for, traditional scouting and human judgment. Therefore, clubs should invest in training traditional scouts and coaching staff to become data-literate and actively involve them in the development and interpretation of AI models. This proactive approach will not only bridge the existing knowledge gap between football and data science but also mitigate cultural resistance stemming from concerns about job displacement and mistrust of 'black-box' systems. By fostering interdisciplinary teams where data scientists, analysts, and football professionals collaborate closely, organizations can unlock deeper insights and ensure that AI outputs are translated into actionable, contextually relevant strategies.

The study confirms that trust in AI significantly predicts fan acceptance and mitigates cultural resistance and authenticity concerns. Developers and clubs should implement XAI to translate complex algorithms into understandable narratives for both staff and fans. Public strategies should highlight AI's benefits, such as enhancing player development and team performance, while transparently discussing its limitations to normalize AI's role and reduce anxieties about its impact on the sport's human aspect.

For smaller clubs with limited resources, forming strategic alliances with external AI consultancies that focus on problem-solving rather than merely data provision may offer a more attainable pathway to developing tailored solutions. Such differentiation, aligned with Blue Ocean Strategy principles, will enable clubs to continuously exploit novel market inefficiencies in player valuation and tactical planning, ensuring their data-driven strategies remain distinctive and difficult to replicate.

Finally, effective leadership and organizational alignment are essential for successful AI integration in professional football. Club leaders must advocate AI by allocating consistent funding and fostering a culture that prioritizes data-driven decision-making and continuous adaptation. This approach requires shifting focus from short-term ROI to viewing AI as a strategic, long-term asset, enabling organizations to develop dynamic capabilities for seizing emerging opportunities, making agile decisions, and reconfiguring resources in a rapidly changing technological environment.

5.2 Limitations

This dissertation is subject to inherent limitations that must be considered when interpreting its findings and assessing their generalizability. The limited timeframe restricted observation of long-term impacts and evolutionary dynamics of AI within football. Additionally, the football industry's closed nature and the novelty of AI constrained the depth of available literature.

5.2.1 Expert Interviews

Semi-structured expert interviews are subject to methodological limitations. The interview guide, developed through an inductive process guided by the literature review, may have introduced researcher bias in question framing. Although expert quality was generally high, the industry's closed nature and AI's novelty in football posed additional challenges. One expert responded in written form, limiting interactive discussion. While qualitative content analysis provided a systematic approach, interpretive and translation bias might have affected the coding and analysis due to linguistic nuances.

5.2.2 Survey

The consumer insights survey, conducted via self-reported online data collection, has limitations in data accuracy. Respondent distribution was notably skewed towards Germany (72%), limiting the generalizability of findings. The sample consisted predominantly of young adults (80% aged 18-34) and males (76%). Additionally, the use of Likert scales may introduce acquiescence bias, affecting response validity.

5.3 Future Research

Limitations of this research, alongside the rapid evolution of AI technology and the dynamic football industry, open numerous compelling avenues for future research.

To enhance the generalizability and robustness of findings on fan acceptance, future research should involve larger, more diverse samples. Given the nascent stage of sophisticated AI adoption in professional football, longitudinal studies are crucial to track AI's evolving impact on perceived usefulness, trust, cultural resistance, and integration.

Future research should explore specific AI applications and their nuanced effects across football management domains. While this study focused on scouting and performance analytics, AI's potential extends to tactical decision-making, player health and injury prevention, fan engagement strategies, and commercial operations. Investigating decision-making at various organizational levels would clarify its transformative effects. Additionally, developing best practices for interdisciplinary teams and human-AI collaboration, as well as addressing ethical, regulatory, and industry standards, are essential as AI integration advances.

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Appendices

Appendix I: Interview Guide

The following guide outlines the core questions that were posed to the various experts during the interviews. As these were semi-structured interviews, it is important to note that some questions were adjusted based on each expert's position and area of expertise.

Current Practices & Understanding

Q1: Can you briefly introduce your role and your experience with scouting or performance analytics in football?

Q2: Could you describe how data science contributes to scouting and recruitment at your club? And what does your collaboration with scouts, analysts, and decision-making look like?

AI Integration in Scouting & Analytics

Q3: To what extent do you use machine learning or AI models in evaluating or predicting player performance?

Q4: Is AI used more for early filtering or for validation of traditional scouting?

Q5: What are the main drivers and most promising opportunities you see for AI adoption in scouting or performance analytics?

Q6: Are there limits to what AI can currently capture, such as intangibles like mentality or tactical intelligence?

Q7: How do decision-makers in your context currently balance data-driven insights with human judgment?

Challenges and Limitations

Q8: What do you see as the biggest barriers to adopting AI-driven scouting?

Disruption Potential & Competitive Advantage

Q9: Do you believe AI could fundamentally change how talent is identified and valued?

Q10: In your opinion, could it give smaller clubs a competitive edge (similar to how Moneyball once did)?

Q11: If AI becomes widely adopted across clubs, do you think this would eliminate/neutralize the competitive arbitrage that Moneyball-like approaches initially offered, particularly to underdog clubs?

Q12: What do you think will differentiate successful AI adopters in the future?

Appendix II: Survey Questions

Table 25 - Survey Questions Outline

Q No.	Question	Question Type	Answer Options
Demographics & Football Engagement			
1	What is your age range?	Multiple Choice	Under 18, 18–24, 25–34, 35–44, 45–54, 55–64, 65+
2	What is your gender?	Multiple Choice	Male, Female, Non-binary, Prefer not to say
3	In which country do you currently live?	Multiple Choice	*List of countries*
4	How closely do you follow professional football?	5-Point Likert Scale	Not at all (1) – Very closely (5)
5	Have you ever heard of the "Moneyball" concept in sports?	Multiple Choice	Yes, No, Not sure
Awareness of AI in Football			
6_1	How familiar are you with the use of data analytics in football scouting or performance analysis?	5-Point Likert Scale	Not at all familiar (1) – Very familiar (5)
6_2	How familiar are you with AI being used in football scouting or performance analysis?	5-Point Likert Scale	Not at all familiar (1) – Very familiar (5)
7	In which of the following football areas do you believe AI is most useful? (Select all that apply)	Multiple Choice (multiple selections possible)	Scouting players, Performance analysis, Injury prediction, Match tactics, Fan engagement, Other (specify)
Perceptions of AI in Football			
Perceived Usefulness			
8_1	AI in scouting helps clubs to evaluate and sign better players	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
8_2	AI-driven scouting is more objective than traditional scouting.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
8_3	AI can identify undervalued talent better than human scouts.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
Trust in AI			
9_1	I trust AI to accurately evaluate players' talent.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
9_2	I trust AI to adequately analyze player performance.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
9_3	AI-based decisions (e.g., player transfers) are reliable.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
9_4	To ensure data quality, please select "Agree" for this statement.	Control Question	Strongly Disagree (1) – Strongly Agree (5)
Perceived Authenticity Loss			

10_1	AI in scouting makes football feel less human.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
10_2	AI in performance analysis reduces the passion of the game.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
10_3	AI-driven decisions undermine the authenticity of football.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
Cultural Resistance			
11_1	The use of AI turns football less interesting and less emotional	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
11_2	AI in football conflicts with the sport's traditional values.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
11_3	Relying on AI for decisions reduces the emotional connection and engagement with football.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
Acceptance & Behavioral Response			
12_1	I support my club using AI for acquiring players.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
12_2	AI influencing club decisions would affect how closely I follow my team.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
12_3	I would encourage my club to use AI for decision-making.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
Perceived Impact & Disruption			
13_1	I believe that AI can give smaller clubs a competitive advantage (like in the original Moneyball concept).	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
13_2	AI has the potential to disrupt how talent is identified in football.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
13_3	In 5–10 years, AI will be essential to professional football clubs.	5-Point Likert Scale	Strongly Disagree (1) – Strongly Agree (5)
Final Reflection			
14	Which of the following best describes your view on AI in football?	Multiple choice	Enthusiastic, Curious but cautious, Skeptical, Opposed
15	What are your main concerns or excitement about AI in football scouting and performance analysis?	Optional Question	Open Text Field

Appendix III: Summarized Expert Interviews

The summarized expert interviews are presented on the following pages. Due to anonymity, the first question about the experts' background was omitted. A List of all experts can be found in Chapter 3 (Table 1). The interview guide, including the core questions, is presented in Appendix I.

Interview 1

Q2: In player recruitment, AI is predominantly used for early filtering. The AI models and analytics teams identify for example a 'top five' list of players for each position. Scouts then go to evaluate these specific players, rather than searching broadly. This means the AI provides a data-driven profile, and the scouts' role is to verify is the player fits that profile in person. Some progressive clubs, such as Liverpool, Brentford, and Brighton are more heavily integrated with data and might be more inclined to trust the data's recommendations, potentially reducing the role of traditional scouts.

Q3: My conversations with clients and people from the industry highlight a strong focus on building models that can predict future performance, moving beyond reliance on historical. Data. These predictive models are becoming 'frighteningly accurate' and are continuously improving. There is ongoing work to capture more qualitative 'human traits,' such as a player's off-ball movement, impact on xG by presence alone, or tactical intelligence, although these are currently very difficult to quantify. For example, 12 Football is making significant strides in predicting how players perform when moving between different leagues. AI models are also applied to sports science, tactics, and competitor analysis to speed up preparation and remove human emotion from strategic decisions. I heard of a PhD student who developed a model to predict non-impact related injuries, allowing coaches to proactively rest players.

Q4: Currently, AI is primarily used for early filtering to identify potential players, after which traditional scouting methods are employed for validation. The AI narrows down the options, making the scouts' work more targeted.

Q5: The main drivers and opportunities include: The ability to predict the future with high accuracy; Removing human emotion and bias from decision-making processes, as scouts can be influenced by external factors like a bad day or long travel; Performing existing tasks quicker and more efficiently; Asking more nuanced questions about a player's fit within a specific team, manager's system, or even specific club, rather than just general league performance; In tactics, AI could reduce a week's worth of preparation to just five minutes by analyzing opponent teamsheets and suggesting optimal counter-strategies.

Q6: Yes, there are significant limits, particularly concerning the ‘human element’ that AI is not yet equipped to handle. These intangibles include: A player’s family crisis at home. The mental anguish of an injury or the worry of recurring injuries. External character factors, such as a scout’s observation that a player with a ‘good-looking girlfriend’ implies confidence. These qualitative factors are currently seen as ‘nice to have’ rather than core focuses, as they are more difficult to quantify that numerical data. However, I believe genetic AI could eventually help integrate this scout knowledge into models, as it would be trained to ‘think for itself.’

Q7: For most clubs, the balance involves AI identifying players and human scouts verifying those selections, with human judgement providing the ‘final stamp of approval.’ For data to be more than just ‘decoration,’ decision-makers at the top levels of clubs need to believe in its influence.

Q8: The primary barriers are not purely technological but rather: Cultural resistance as many coaches and recruiters perceive data as a ‘threat.’ One head coach once asked, ‘What can a computer tell me that I haven’t got written down in my little black book?’ Further, soiled teams as data analytics often operates in isolation, not integrated into the broader club structure. Lack of clarity: Clubs frequently acquire tools without clearly defining the problems they aim to solve. Poor integration. Lack of buy-in from the top. The need for quick ROI. The difficulty in quantifying qualitative data. Clubs often prioritize paying players over investing in robust data analytics teams, preferring to build teams around one expert with graduates and juniors due to the ‘lure of football’ leading to lower, uncompetitive salaries for data professionals.

Q9: Yes, absolutely and definitively. Many clubs are still lagging behind, needing to catch up to trendsetters like Liverpool, Brentford, and Brighton. I anticipate a significant shift where data experts become ‘football literate,’ rather than the current focus on sports scientists and scouts becoming data literate.

Q10: Yes, AI could definitely provide a competitive advantage, especially for smaller teams, much like the Moneyball approach did for the Athletics in baseball. Currently, the advantage is simply ‘we're using AI and you're not’.

Q11: No, I believe it will ‘change competition’ rather than eliminate it. If all clubs use AI in the same way with the same criteria, they would all identify the same players, turning it into a bidding war for who can pay the most. Therefore, clubs will need to become ‘more clever’ and employ ‘different parameters’ that their competitors are not using. In the future, the advantage will shift from simply ‘using AI’ to ‘measuring something that you're not.’ The clubs that are first to innovate in this area will gain an edge, assuming money is not the only factor. This could also lead to clubs specializing in specific systems or coaches and recruiting players that perfectly fit those parameters.

Q12: Future successful AI adopters will be differentiated by: Their ability to use ‘different parameters’ and measures that their competitors are not yet employing. Being the ‘first’ to identify and leverage new metrics or data points. Investing more heavily in and attracting stronger data experts in the field. The transition to having data experts who are deeply ‘football literate’ will be a key differentiator.

Interview 2

Q3: In my academic research, I develop and apply AI models to football. For instance, I’ve worked on models to predict tracking data from event data and to predict injuries. A significant part of my work involves player evaluation, particularly for defenders, where I. explore using AI to measure off-ball metrics, such as positioning, which are traditionally hard to quantify. I’ve observed that some clubs utilize AI models like VAEP, which evaluates on-ball actions by predicting their probability of leading to a goal, providing a more advanced player evaluation than just goals and assists.

Q4: From my understanding, AI is primarily used for early filtering. It helps to narrow down a vast pool of potential players to a more manageable selection, which then allows human experts, coaches, and scouts to focus their efforts for further validation.

Q5: I see several main drivers and promising opportunities for AI adoption: Initial player evaluation and screening. Injury prediction and prevention, AI can assist medical departments in optimizing team lineups and better predicting injuries. In-game modelling, although very difficult and still an evolving area, AI has the potential to optimize real-time decision-making during a game, evaluate team performance, and suggest tactical changes.

Q6: Yes, there are significant limits to what AI can currently capture, particularly regarding intangible human elements. The main challenge lies in collecting accurate and sufficient data for these aspects. For instance, it's hard to collect data that accurately predicts how a player will adapt to a new country or environment. While AI could potentially use such data if collected, the difficulty is in the data collection itself. Currently, AI models cannot precisely capture a player's psychological state, daily feelings, or general fitness in the way a human expert like a coach can. Therefore, I believe it's essential to combine AI with human input, adopting a 'human in the loop' approach.

Q7: I believe the current balance involves a combination of AI and human input, where AI informs decision-making rather than completely replacing it. There's often a 'missing point' between data science teams and coaching teams, where AI outputs are challenging to interpret or don't always translate directly to what coaches observe on the training field. For example, an AI model might predict a player is at high risk of injury, suggesting they should be rested, but human judgment is still necessary to convince the player and make the final decision. It's about using AI information on top of existing human insights.

Q8: Insufficient data: There isn't enough comprehensive data to model all the intricate aspects of football, especially for complex human elements like psychological state or fitness. Interpretability of AI models: Many AI models are 'black box' models, making them hard to interpret, explain, or prove statistically. This leads to resistance from coaches, managers, and even fans who may not trust numbers that don't align with their perceptions or what they observe. Gap in understanding: There's often a disconnect where data science insights don't translate effectively to coaching teams, creating a 'missing point' between departments. Football's lagging adoption: Football is generally behind other industries and sports (e.g., American sports) in adopting AI and data science. Unpredictability of the sport: Football's low-scoring nature and high unpredictability make it challenging to justify AI model outputs compared to sports with more frequent, measurable events. Cultural resistance: Overcoming the subjective and opinion-based nature of football and building trust and understanding between data science and coaching teams is a significant challenge.

Q9: Yes, I believe it will fundamentally change how scouting is done. AI will primarily serve to narrow the scope of scouting by providing a strong data-driven starting point. The final decisions will likely be made by a combination of human experts and AI outputs, with AI having a significant influence on which players are shortlisted.

Q10: Yes, I think AI could benefit smaller clubs. It would make it much easier for them to scout players in more distant or lesser-resourced leagues where data is available, without incurring the high costs of sending human scouts. This would significantly increase their scouting scope. However, I also acknowledge that larger clubs would likely gain similar benefits, making it an open question whether it would ultimately level the playing field or create a new balance.

Q11: Yes, there is an element of neutralization if all clubs use the same techniques and data. If everyone converges on the same statistics, it would simply become a new standard set of metrics rather than a competitive advantage for any single club. The advantage would then shift to clubs with in-house departments that are innovating or 'doing different things' or those who are 'further along in the state-of-the-art.' This is comparable to the advantage of having the best coaches; similarly, having the best data scientists would provide a competitive edge. I believe the importance of attracting and building a strong data science team will grow significantly, though players will always remain the primary focus.

Q12: I believe successful AI adopters in the future will be differentiated by: Their ability to implement in-house departments that are more advanced or employ unique methodologies compared to competitors. Their success in attracting and retaining top data scientists, as this will become a crucial competitive battleground for clubs. Their commitment to integrating data into their entire process and all decision-making, as I anticipate all clubs will eventually need to adopt this approach to remain competitive.

Interview 3

Q2: For data science to truly make a difference, you need strong alignment from ownership and sporting directors. Without that strategic buy-in, even the best systems often fail. Clubs like Brighton, Brentford, and Liverpool are good examples of effective data use. It's also critical to document internal processes to make systems club-dependent, not individual-dependent, so you don't lose knowledge when people leave. Decision-making should always be an 'and' approach, combining data, video, and traditional scouting for the final call.

Q3: Honestly, AI is often just a ‘buzzword’ in football right now. Many claim to use it, but without deep implementation. Sometimes, simple, well-understood data is far more effective than overly complex, poorly applied AI. The real power comes from merging deep football understanding with data science expertise.

Q4: Data, and I expect future AI, should primarily act as an early filter. It helps narrow down the massive player market for traditional scouts. But yes, it can also be used to validate players that have already been identified through conventional scouting.

Q5: I see the biggest opportunities as football data evolves. We're moving from just event and tracking data to ‘body composure’ data – things like positioning, head direction, and body posture. When you combine these data types with large language models and AI, I think we could really ‘dig deeper and find patterns’ in scouting and even training. We already have models that can predict how a player's performance might translate between different leagues, though these always give you probabilities, not certainties.

Q6: Absolutely. AI currently struggles to capture intangibles such as a player's character, mentality, or how adaptable they'll be to a new country and culture.

Q7: It's all about that ‘and’ approach. Data starts the filtering process, then you go deeper with more data and video analysis, and finally, traditional scouting comes in for those crucial final decisions.

Q8: There are many, but a huge one is cultural resistance. Sporting directors and traditional scouts often fear for their jobs if data and AI come in. A critical factor is a lack of ownership involvement and strategic alignment. Then there are the high costs for data scientists, engineers, and the data itself; smaller clubs often prioritize buying players instead. You also have reliance on traditional methods and agents, and that ‘buzzword’ problem leading to distrust. Finding and keeping multidisciplinary talent (data science plus football knowledge) is really tough and expensive. I also believe in the professionalization of sporting management, moving beyond just hiring ex-players for top positions.

Q9: Yes, despite its current "buzzword" status, I believe AI has ‘big potential’ to fundamentally change talent identification and valuation.

Q10: Absolutely. Data science and AI can provide a competitive edge for smaller clubs. For instance, we supported a small English club's incredible rise to the Premier League by helping them identify undervalued players using data. This definitely requires a mindset shift towards investing in robust systems.

Q11: Yes, I do anticipate that this competitive advantage will diminish after a while if AI becomes widely adopted. However, early adopters and innovative clubs will always be looking for 'what's next,' continuously creating new advantages. Most clubs, though, really need to focus on properly adopting basic data science first.

Q12: Successful AI adopters will be differentiated by early adoption and continuous innovation. They'll need effective internal utilization and documentation of their processes, strong strategic alignment and genuine ownership buy-in, and the ability to attract and retain top data science talent who also understand football. The professionalization of sporting management will also be absolutely key.

Interview 4:

Q2: In a professional club, alignment is crucial, just like in a company. Data scientists need to understand the football context to make their work useful. The trend is changing; clubs like Brighton and Brentford, for example, are now replacing traditional scouts with people who understand data. For me, success comes from balancing experienced football eyes with data. I always say, I will never sign up a player if the data says no. Data tells you how your manager plays and the team's style, but you also need market knowledge. We use tools like Wyscout and Hudl for analysis and video scouting.

Q3: We actually use an AI tool that we built ourselves with a team of engineers, customized to our style of play and what we look for. We teach the AI tactical concepts, feeding it video clips and documents, so it learns our preferences. This allows us to not only scout and analyze but also to predict how a player will perform within our system and how rival teams might act against us. I don't manage all the machine learning myself; we have a dedicated person for that.

Q4: It's primarily used for early filtering. We first look at the data, often using AI processes, to filter through players. It helps us narrow down the market based on our specific requirements and style of game. It also serves to validate players by seeing if they adapt to our game and style.

Q5: For me, AI is an 'assistant,' not a replacement. Its main advantage is to help with fast decision-making by quickly providing and relating different sources of data. It helps scouting and analysis departments, and frankly, any department in a football club because a club is a company. AI can also generate dashboards, which saves a lot of time and money compared to manual data entry.

Q6: Our AI, which is still being built, sometimes struggles to interpret the full context of a game. It might measure individual actions but not fully grasp how a team is defending or the overall tactical system. This is more of a challenge than a limitation, requiring constant training and feeding the AI with comprehensive context for it to truly understand the game.

Q7: It's a balance. My rule is: I will never sign up a player if the data says no. Even if my experience and understanding of the market suggest a player could be good, the data must support it. You need the knowledge of the market and experience, but data is essential to validate your arguments and decisions.

Q8: The main barrier is cultural resistance. Many people, even from newer generations, still feel 'threatened by data' and AI because they have their own way of understanding football and don't want AI to dictate their decisions. Not all clubs are adopting it; I've been in touch with teams in Greece or Cyprus where managers, sports directors, and presidents simply don't trust or like data. This lack of buy-in from the top is a significant hurdle. However, it's a matter of time; if clubs don't accept it now, they'll fall behind.

Q9: Yes, absolutely. I believe AI will fundamentally change scouting and analysis. It will save a lot of time and money for institutions by automating analysis and dashboard creation.

Q10: 100% yes, it will make a difference. Big clubs already use it, but smaller and medium clubs choosing to build a good model with data scientists, good scouts, and trusting AI/data processes will gain a significant advantage. If even a third-division team applies and invests in this, it will differentiate them from the rest.

Q11: It depends a lot on how you use it, how you feed it, and how you train it. Not every club will use the same AI models or data sources. Some clubs only visualize data and don't really go deep into the models; they use it because they have to, not because they truly integrate it. So, the advantage will likely persist for those who implement it effectively and innovatively.

Q12: What will differentiate successful adopters is how they truly use, feed, and train their AI models and processes. It's not just about having AI, but about developing customized solutions and deeply integrating the technology to adapt to their specific needs and philosophy. Clubs that only superficially adopt AI won't gain the same competitive edge.

Interview 5

Q2: At my club, the process starts with the raw event data. We collect event data from over 100 competitions worldwide, resulting in about 3,000 events per match. From this data, we compute around 350 total metrics. For a specific player position, about 30-40 of these metrics are relevant. We use machine learning models to determine which of these metrics are important for winning games in a given position. Player roles are defined by expert opinion. Machine learning then identifies which metrics are crucial within that defined role.

This data-driven approach generates an initial shortlist of players who fit the specific role, considering factors like league level and affordability. This list is then passed to the scouts, who focus on intangibles that data cannot measure, such as mentality, behaviour on the pitch, character, and physical attributes. The final recruitment decision is made collaboratively by the technical director, chief scout, head coach, and a member of the data team.

Q3: We primarily use machine learning models to determine which metrics are important for a specific player position. For instance, if we're looking for a right winger or a center-back, our model identifies the most crucial metrics out of the 350 we track. We define "important" as metrics that, based on historical data, have a high correlation with winning games.

Q4: AI and data are mainly used for early filtering. We employ a ‘data first’ approach, where data acts as the initial filter to identify suitable players. I estimate that 95% of the players we consider come from these data-generated shortlists. However, if we receive external player proposals, such as from agents, we first use data to verify if the player is good enough before dedicating human scouting resources to them.

Q5: I see two main opportunities for AI adoption. The first are Chatbot-like Interfaces: With the emergence of tools like ChatGPT, I believe AI can facilitate chatbot functionalities. This would allow scouts to directly query the data (e.g., 'Give me the 10 best right wingers under 5 million'), which would reduce manual work for data scientists and make insights more accessible to scouts. The second 'AI Sporting Director': I envision optimization algorithms that could function as an 'AI sporting director.' These algorithms could suggest the optimal players to recruit to maintain team performance if a player were to leave, by considering factors such as age profile and personality, provided such data were available.

Q6: Yes, there are three key limits, all stemming from a 'lack of data': First, Player Character and Personality: There is no objective data to measure a player's behavior on the pitch, their personality in the dressing room, or leadership qualities. Scouts currently rely on observing games and speaking with network contacts to assess these 'intangibles.' Second, Physical Data: Widespread physical data for players outside of a club's own league is often unavailable. While clubs may request this data during negotiations, it is not always shared. Third, Off-ball Actions (Tracking Data): Event data captures on-ball actions, but tracking data (player positions at every second) is needed for off-ball context. However, tracking data is extremely expensive, making it inaccessible for many clubs across all desired leagues.

Q7: We employ a 'data first' approach. Data is used to generate an initial shortlist of good players, allowing human scouts to then apply their judgment to subjective factors like mentality, physical output, and character, which are not quantifiable by data. The ultimate decision for recruitment is a collaborative effort involving the technical director, chief scout, head coach, and a data team representative.

Q8: I believe the 'buy-in from the top' is by far the 'biggest bottleneck'. I've observed that clubs with American ownership, like Casa Pia and Spezia, readily adopt data-driven approaches due to common practices in American sports. However, I think that 99% of the clubs are still run by 'traditional football people.' Many of these individuals either don't recognize the value of data, or they lack the financial resources or willingness to invest in it, even if they have the money, because they don't fully understand what it could bring them.

Q9: Yes, for clubs that are not yet working with data, AI could fundamentally change how they are operating for sure. I also think that for clubs already utilizing data, the primary distinction remains between those that use it and those that do not, as most data-using clubs are doing it all well mostly, while others are basically behind.

Q10: Yes, I believe AI can provide a competitive edge to smaller clubs. While larger clubs can simply buy top players, smaller clubs benefit from a much larger pool of 'good enough' players to discover. Data allows these clubs to identify many interesting players, such as free agents, that their limited number of scouts might otherwise miss. This enables their few scouts to focus specifically on players already deemed relevant by data. I remember at one of my previous clubs, in the first season, we built a squad mostly with players who were free agents or released from their previous clubs by using data.

Q11: I think that if data-driven recruitment becomes widespread, the competitive advantage will shrink, possibly down to a '1% difference' based on model quality, similar to what happened in baseball. I believe the new competitive advantage would then shift to outside of recruitment, focusing on 'optimizing the match day performance.' This involves using data for tactics and decisions made before and during games, an area where I think almost no one does extensive work, with perhaps not more than 20 clubs worldwide currently doing so.

Q12: I believe that once data-driven recruitment is widespread, the key differentiator for successful AI adopters will be their ability to leverage data for the performance side. This means focusing on how data can be used to help the first team 'perform in the most optimal way' through pre-match analysis, post-match analysis, and making in-game decisions.

Interview 6

Q2: I believe data science makes a significant contribution and provides enormous competitive advantages, especially for larger clubs. It offers us the ability to track and evaluate nearly every player globally where data is accessible, which means we can assess players from leagues like Honduras or Venezuela, something traditional scouting can't achieve on that scale. In terms of decision-making, it helps us reduce inherent bias, provides predictive models, and uncovers hidden patterns that complement our scouts' analysis. Ultimately, it's about supporting and enhancing human judgment, as there are still many aspects, like psychological analysis or relationships, that data can't fully capture yet.

Q3: Well, it's a bit challenging to give specific details from my club, as the football world is quite closed about its developments. However, generally, machine learning is utilized in computer vision to gather tracking data and in various models for player evaluation. We see examples like 12's LLM model being advertised, and Liverpool's past collaboration with Google's DeepMind on a set-piece model using deep learning. But broadly, clubs tend to keep their discoveries and models secret, so published research on scouting models is scarce compared to performance data like GPS.

Q4: I see data being integrated effectively at both the beginning and the end of the scouting process. At the outset, it's incredibly useful for identifying players and generating shortlists, which saves a considerable amount of time. Towards the later stages, data models serve to complement scout observations by helping to reduce potential biases and reveal hidden patterns. In an ideal environment, these insights can support, or even challenge, existing decisions, fostering continuous improvement.

Q5: The most promising opportunity, in my view, lies in developing even more sophisticated predictive models. The continuous emergence of new and better data, particularly event and tracking data, is a primary driver pushing this forward. However, one of the biggest challenges remains accurately predicting player development, as it's a non-linear process, with players peaking at different ages – just look at a case like Jamie Vardy. Intangibles like psychological analysis or how players react to the public are also still very difficult for AI to predict.

Q6: It struggles to capture intangibles like a player's mentality, personality, psychological profile, their relationships with teammates, or their reactions to public pressure. Furthermore, football itself is a chaotic, low-scoring game on a large pitch with relatively few players, which makes implementing certain models more complex compared to a sport like American football. While technical and tactical aspects are becoming easier to analyze with data, quantifying certain positions, like a center-back, is still more difficult than evaluating a striker.

Q7: In my experience, data-driven insights are primarily used to support and complement human judgment. Our models help to reduce potential biases and uncover patterns that might not be immediately obvious, enhancing the overall analysis. Ultimately, areas like psychological analysis and understanding the specific context of a player remain crucial and are best handled by human scouts, as these are aspects data cannot fully reach yet. If data and scout observations differ, a healthy club environment should encourage re-analysis rather than dismissing one over the other.

Q8: I'd say the biggest barrier is the 'cultural side': the willingness of owners and directors to genuinely embrace data-driven decision-making. In Southern Europe, for instance, many clubs are less open to these new approaches compared to those in top English divisions, where data is more widely spread. The second major barrier is financial capacity; data providers are extremely expensive, and smaller clubs often simply cannot afford both the necessary data and the skilled personnel to handle it. Even with the best data and teams, if the insights aren't truly valued and acted upon by leadership, they're useless.

Q9: Yes, I definitely believe AI has the potential to fundamentally change scouting in football. It's a transformative force, much like when Wyscout and other companies began providing global video footage of matches, revolutionizing how scouting was done. Data possesses that same power to transform talent identification and decision-making analysis, which is why top clubs are continuously investing more in both people and data.

Q10: My opinion is that bigger clubs will likely maintain or even gain a greater advantage. This is primarily due to their financial capacity. They have the means to invest heavily in expensive data providers and to hire larger, more skilled data science teams. Smaller clubs, particularly here in Portugal, often face significant financial struggles, meaning that investing in costly data and personnel isn't always a priority or even an option for them.

Q11: Even if AI becomes widely adopted and every club, theoretically, has access to top-level models, I still believe the best clubs will always find ways to secure a competitive advantage. We've seen this throughout history with other advancements in scouting and performance analysis; the top clubs usually adapt faster and innovate further. Crucially, the willingness of club owners to truly embrace and correctly utilize data-driven processes remains key. If insights are ignored or misused, even the most sophisticated models and data science teams become ineffective.

Q12: For me, the key differentiator for successful AI adopters in the future will be the willingness of owners to genuinely embrace and correctly utilize data-driven processes. It really comes down to this cultural aspect we discussed earlier. Having the best models, the most talented data science teams, and access to the best data means very little if those insights are then ignored or not applied properly by the club's decision-makers.

Interview 7

Q2: Data integration into first team scouting has evolved significantly over the last few years. Big clubs now have strong data quality and modelling. With more American influence and a senior management approach, clubs are increasingly taking decisions based on data. Data is a major contributor to modelling ideal decisions, and I believe good decisions can't really be made without data integration, especially in an international context. Nearly every decision-making process can be improved by involving data correctly.

Q3: At the moment, I would say our use of machine learning or AI models is still at a relatively low level compared to other industries. The market dynamic in football transfers is nearly impossible to anticipate, making it hard to model things like team chemistry. There are just too many variables that are difficult to control or estimate correctly. However, in other disciplines like performance management, such as injury prevention or measuring youth players' speed development, AI tools are already in place and deliver important insights.

Q4: Players actually come onto our lists much earlier through data scouting, which runs before video or live game impressions. However, it's not always about just collecting or filtering big data sets; often, we look at one thing very detailed. If we're unsure about an aspect, like a player's transition to another league, manual work is still done. The current limitation is a not yet established workflow that covers all these aspects.

Q5: I see three main opportunities for AI in scouting. Firstly, in character insights, AI tools could deliver insightful reports by combining public and match data to understand player reactions and performance, as much of this is currently manual. Secondly, for individual performance, while detailed data exists, AI can translate this information into LLMs to make it accessible and understandable for different stakeholders, like board members who prefer short written texts over numbers. Thirdly, in modelling the influence of players or coaches, this remains the most difficult field due to many variables and off-pitch factors that are nearly impossible to anticipate. Football's low-scoring nature and 11-vs-11 setup also make it less data-friendly than other sports.

Q6: When it comes to intangibles, training a machine to get relevant information out of big data sets will potentially be quicker. However, from a sheer scouting perspective, I rarely need all fields of information to complete my personal picture of a player; often, I'm focusing on one specific detail. The main limitation is a not yet established workflow that covers all aspects. There's also a high danger of AI taking too many things into account and creating improper models. While I see the possible speed increase that AI could generate, I would challenge it to deliver the same specific insights I gain manually.

Q7: Good decisions can't really be made without data integration, especially in an international context. The most critical factor is top management and how decision-makers emphasize data to make it an integral part of the process. For instance, I've seen clubs with good data departments where 80% of decisions were made without data, leading to bad outcomes. It's fundamentally about modelling the right process and having a workflow where data cannot be overlooked.

Q8: The biggest barrier is absolutely top management and how decision-makers emphasize data to make it an integral part of the process. I've observed Bundesliga clubs with excellent data departments making 80% of decisions without data, which resulted in many poor choices. It's essential to model the right process and establish a workflow where data cannot be bypassed. The involvement of key figures like the managing director of sports or the head coach is crucial; otherwise, the data department might be entirely sidelined.

Q9: I actually believe the opportunity and potential is bigger for smaller clubs. Their leverage effect will be higher because big clubs already have such profound data departments and analysis. AI will likely democratize data in sports, making it easier and cheaper for smaller clubs to profit from certain data sets and analysis. I anticipate that the next 3-5 years will bring cheaper and more effective solutions to the market, helping to reduce the gap to bigger clubs.

Q10: Yes, I think the opportunity and potential is bigger for smaller clubs. Their leverage effect will be higher because big clubs already have such profound data departments and analysis. AI will likely democratize data in sports, meaning smaller clubs could more easily buy into data sets and profit without needing extensive data analysis teams. I anticipate cheaper and more effective solutions in the next 3-5 years that will help reduce the gap to bigger clubs.

Q11: I'm not sure if the competitive advantage will be neutralized, but I do think there is potential to make the gap smaller. The main differentiator will be modelling the right decision-making process, even if data tools become widely available. Success depends on at which point data is involved among key decision-makers and their familiarity and speed in communication using those insights.

Q12: For me, the key differentiator for successful AI adopters will be modelling the right decision-making process. It's crucial at which point data is involved among the key decision-makers, such as the chief data analyst, chief scout, sporting director, and CEO. Their familiarity with dashboards and their speed in communication to create a comparative advantage will be vital. This includes anticipating market trends and securing signings ahead of competitors. Decision-makers need data translated into understandable formats, whether words, dashboards, or diagrams, to truly be informed and engaged in player recruitment.

Interview 8

Q2: I believe the main application of AI or data science in football is scouting. It's a smart move to use data because nobody can watch enough football to find all good players. Clubs' approaches vary based on their culture; some want to confirm existing opinions, others build data processes from scratch, or simply double-check their work. In decision-making, most clubs aren't using data efficiently. They may have data but struggle to transform raw data into useful information, leading to a lack of trust from decision-makers. There's a significant gap in the industry, with data maturity varying greatly by league and club.

Q3: After building a basic data infrastructure and doing initial data science tasks, the next step for most clubs is to go predictive with machine learning and AI algorithms. I estimate that around 20% of clubs with structured data have already moved to guided and good machine learning models. While all clubs can easily build an xG model, this ‘next step’ is not universally adopted. Many models focus on predicting the value of actions on the field, like xG for shots, which can be combined to create new metrics. It's also possible to predict player value, injuries, and physical outcomes.

Q4: When consulting, we often help clubs establish their basic data department. The maturity of football clubs varies significantly, unlike in basketball or baseball where most clubs have already mastered the basics and moved to ML/AI models. There are two main ways predictive models are used: clubs with basics can create shortlists with metrics and then consult us for predictive insights, or some clubs use their own predictive models to generate new metrics for scouting shortlists. Companies like Gemini Sports Analytics also provide a single player score from various predictive models for shortlisting. However, in my opinion, this single-score strategy doesn't work as well in football as it does in basketball.

Q5: The football industry is currently not fully aligned with newer AI technologies like LLMs (ChatGPT, Gemini). I believe a significant opportunity for scouting is to integrate LLMs with scouting reports. This would allow us to generate a phrase or description of a player's style, strengths, and weaknesses instead of just showing videos or raw metrics. The goal is to integrate databases and models with LLMs to provide words instead of raw numbers. Some work already done by teams like Sevilla demonstrates this potential.

Q6: I see two primary limitations: the quality of data and the availability of skilled people. Football's dynamic nature means data isn't always good enough to be the best predictor; we can't fully capture things like a player's field vision. There are also computational challenges in detecting player post-data. The second limitation is a shortage of people who are knowledgeable about AI tools and can build scientifically robust models. We need more data scientists to process information correctly and ensure proper data digestion. As Luke Bourne often says, having a good process with bad data is preferable to good data with a bad process.

Q7: This is, in my view, the toughest part of the job. While we've had success with one data-aware club, with most, every step forward feels like two steps back. Football's deep cultural roots in many countries often lead people to disbelieve or reject data-driven approaches. Many decision-makers are not open to these methods, either out of fear (like in Moneyball) or simply due to unfamiliarity. This fundamentally requires a significant change in the club's internal culture.

Q8: I believe the cultural barrier within clubs remains the biggest obstacle. There's a lack of awareness about the long-term importance of investing in data scientists, who are expensive but offer substantial future gains compared to player costs. Clubs often lack a long-term vision due to short-term thinking from supporters. A club's internal culture must be very strong to prevent external pressures from derailing its data-driven processes. In Brazil, I've seen supporter and press pressure lead owners to make non-data-driven decisions, highlighting the need for a very strong foundation.

Q9: Yes, I believe it has already fundamentally changed things, though people may not always see it happening in the background. Clubs like Brighton and Brentford are entirely data-driven, and they have consistently moved from the Third Division to the First Division. The adoption of this change is slow across different football cultures. I am eager to see what the scenario will be like when every club eventually adopts these approaches.

Q10: I think club size matters significantly. Larger clubs possess the financial resources to hire top data scientists, analysts, and engineers, allowing them to establish superior processes and accelerate their adoption. Smaller clubs, with their limited technology budgets, may fall behind because they cannot build such infrastructure. However, while data is expensive, smaller clubs potentially have more to gain from it. They also have more room for error, as a smaller budget mistake is less impactful than a large one.

Q11: This is a very broad question, and I don't have a definitive answer. Currently, clubs' models are often kept secret, so we don't know what competitors are doing. The next competitive challenge will be to develop the best models. If every club adopts a data-driven approach, the key differentiator will become who has the best data-driven approach. After recruitment, the next area for competitive advantage will be on the tactical side, making more informed in-game decisions and collaborating with coaching staff. However, I believe we are years away from that level of in-game data utilization.

Q12: The main differentiator for successful AI adopters will be having the best data-driven approach. The next phase for data science will be in-game tactics, focusing on more informed decisions during matches and strategic game planning with coaching staff. Beyond on-pitch applications, data science can significantly aid in the overall organization of a football club. This includes data-driven pricing for tickets and using data in the marketing department to optimize social media engagement, which in turn can generate more revenue and advantage. These are currently less explored areas that could offer a unique edge.

Interview 9

Q2: The importance of data science differs significantly between clubs. We invest a lot in it, and I sit next to our data scientist, valuing their opinion highly when I have queries about players. Data is excellent for initially flagging players, which saves a huge amount of time and resources for our scouts. However, we would never sign a player based solely on data; visual scouting remains incredibly important. Data helps guide scouts to watch specific players, but they're still encouraged to report on any other good players they find. Clubs like Brighton and Brentford massively use data and are seeing huge rewards, such as with players like Mbeumo.

Q3: We utilize data systems that involve a lot of coding, though I'm more focused on appreciating what these systems can do and using their visualizations, rather than building them myself. Our scouting system now uses AI to condense multiple reports on a player, summarizing their key strengths. I wouldn't say we use AI massively yet; it feels like it's still 'teething' and there's a general wariness about what it can do. From my personal experience, we don't currently use AI to evaluate or predict player performance. Most of our current systems are coded and developed either internally or by external data companies.

Q4: The data is primarily used for initial flagging to create a shortlist of players for scouts to view. We intentionally don't tell scouts why a player was flagged to prevent bias and ensure they provide their own subjective opinion. While data helps, I believe it's vital for scouts to offer their personal judgments to avoid the process becoming 'robotic.' Data also complements video and written reports in presentations, providing backing evidence, although it won't be perfect 100% of the time and discrepancies are noted.

Q5: I don't want AI to eliminate jobs, but it offers significant opportunities to develop scouting and data systems. Scouting has evolved dramatically in 20 years, and I anticipate that in another 20 years, AI might create recruitment videos or instantly generate reports. The goal is to expedite the process, allowing us to assess more players quickly and identify who is suitable. However, I believe AI should be used cautiously and in conjunction with subjective, personalized opinions; we shouldn't over-rely on it.

Q6: Absolutely, there are definite limits; AI cannot capture intangibles like leadership or personal qualities. You can't get a reference from AI about a player's off-pitch life, family, or their impact in the dressing room. Watching a game live often reveals elements, like shouts or how a player controls the game, that video might miss. AI should supplement the scouting process, not take it over, especially since much of my work is subjective. It's still very early days for AI in football, so we need to proceed cautiously.

Q7: In my view, AI should be used very cautiously and in conjunction with human judgment, not to override it. While data can support our visual observations, it's not perfect every time, so human judgment is essential to interpret any discrepancies. My personal experience heavily involves visual scouting and subjective opinions. For any new process, it's crucial that everyone, from the higher-ups to the recruitment team and scouts, buys into it to ensure it works for the club.

Q8: The biggest barrier is that experienced people at higher levels are wary of using AI, as they are accustomed to traditional, proven scouting techniques. There's uncertainty about its effectiveness, and with millions of pounds on the line for player signings, there's too much at stake to trust something unproven. A wrong decision could cost a club its place in the league. Therefore, AI must be used very cautiously, and widespread adoption requires that everyone in the club, including the leadership and recruitment teams, is on board with it.

Q9: I think claiming AI will completely change it is a very strong statement. It will certainly be used, and it will contribute to the modernization of scouting, much like data models have emerged. However, I can't envision it ever entirely replacing traditional scouting; to me, nothing beats what you see with your own eyes. You wouldn't sign a player based solely on a data report. AI should supplement traditional methods, not completely overtake them. Yet, given the global trend, it wouldn't surprise me if AI becomes a massive part of the process.

Q10: Yes, I believe it would be more beneficial for smaller clubs. Smaller clubs have more flexibility to take risks with players because they're signing them for less money, aiming to develop them rather than buying a finished article. AI could help them identify players who are strong in specific areas, allowing the club to develop them further and sell them for a significant profit. Bigger clubs, like Real Madrid or Man City, don't need this edge as much; they can simply buy established, ready-now players. Smaller clubs have the time to integrate and develop players gradually, which aligns well with an AI-driven approach.

Q11: Yes, I believe it could neutralize the gap between clubs in identifying players. If many clubs use similar data models, they'll likely flag the same players, as we already see with transfer news. When shortlists become similar, the personal aspect of what a club can offer a player becomes paramount. It then comes down to the club's ability to convince a player to join, based on factors like guaranteed game time, development pathways, or a strong personal connection with the manager. It's about the unique value proposition.

Q12: If data models become increasingly similar, leading to the neutralization of competitive advantage in player identification, then the key differentiator for successful AI adopters will be the human side of recruitment. Clubs that can offer players a compelling personal package, such as guaranteed game time, a clear pathway for progression into the first team, or a strong connection with the manager, will stand out. It will be about the club's ability to convince and personalize the opportunity for each player.

Interview 10

Q2: Data science complements scouting operations in most clubs, and it's especially important for smaller clubs. In a well-run club, scouts and data can independently generate player lists based on set criteria. These lists are then exchanged and validated by the other party, creating a good balance of human and data views. While no club makes decisions solely on data, a good sporting director uses data to challenge scout opinions and provide more agency in decision-making.

Q3: Machine learning and AI models are reasonably well-developed in football compared to other industries, benefiting from good data availability for researchers. However, integrating these sophisticated models into decision-making is challenging. While tracking data models are sophisticated, they are expensive to collect and process for relatively marginal gains, making them difficult for most clubs to afford. Event data models are more varied, but areas like injury or financial data are largely untouched due to data unavailability, and even simple models pose implementation challenges.

Q4: I believe data, including AI/ML, serves for both early filtering and validation. Scouts create player lists, and data also generates its own list from set criteria, and these are then exchanged and validated by the other party. If the data shows good numbers, a scout will look at the player, and if a scout says a player is good, the data is reviewed. It's about getting an independent view from each party to challenge each other.

Q5: The main drivers are cheaper and more widely available data. As computer vision improves, it will generate event data more accurately and cheaply, increasing accessibility globally. Similarly, tracking data, crucial for off-ball events like defensive positioning, needs to become commoditized and cheaper to access and process, allowing us to quantify the 97% of events not on the ball. Body pose estimation offers deeper insights into player actions, and if data becomes cheaper, clubs will find ways to adopt these for areas like injury prediction or opposition analysis.

Q7: Decision-makers, especially good sporting directors, weigh the evidence from both data and human scouting. I believe data is used to challenge a scout's opinion or to ask questions that might not have been covered by traditional scouting. This approach provides sporting directors with greater agency in their decisions, moving beyond sole reliance on a person's opinion. However, the football mentality, with its high jeopardy and pressure, can create fear in adopting practices seen as unusual.

Q8: The biggest barriers are cultural resistance, cost, and the inherent jeopardy of European football. Football is very insular, often preferring known individuals and short-term solutions, which hinders data's long-term impact. Companies have also struggled to effectively link the cost of data generation to its decision-making benefits. Furthermore, the high stakes of relegation and promotion in shorter seasons create a fear of experimentation with unusual practices.

Q9: Yes, I believe AI will fundamentally change the nature of scouting, and it's coming soon. As data processing becomes cheaper and access to footage improves, the price of these technologies will decrease, transforming scouting practices. The competitive advantage from data has already been significantly eroded; finding an 'overlooked' talent like Andy Robertson or Mo Salah is rare now as good young players are tracked by major clubs. This edge will further diminish with the commoditization of data. However, football's adversarial nature, allowing diverse playing styles, should prevent a homogenized game, unlike what some argue happened in basketball.

Q10: It depends on a club's definition of success; not all clubs aim to be the biggest in the world. However, I believe there absolutely is a reason for smaller clubs to adopt data, including AI. It's going to become 'table stakes' fairly soon, meaning clubs that don't use it will ultimately fail, regardless of their success metrics. Even if they have a player trading model, data will be essential.

Q11: Yes, I believe the competitive edge offered data approaches has already been massively eroded and will be further neutralized by the commoditization of data. It's now rare to find a talented young player whose data isn't already known by major clubs. However, football's inherent adversarial nature, which allows for diverse playing styles, means there likely won't be a uniform way of playing, which is key to avoiding the homogenization seen in sports like basketball.

Interview 11

Q2: We have developed internal rating and algorithms to help with player scouting, and it's improving day by day. The scouting department now largely agrees with our algorithm's findings; what was once a common disagreement is now in sync about ‘9 in 10’ times. For example, in the current market, we form a team with one data person, one scout, and our sports director to find the best market options. While scouting still holds a ‘much higher opinion’ than us, our data-driven opinions are much more heard now than it was in the past, though the final decision always rests with the Sports director.

Q3: Football is very delayed in terms of technology compared to other industries. At the moment, we haven't reached a point where we are using AI or machine learning on a daily basis at a higher level for player evaluation or prediction. We are not against it and believe it will be a great help in the very near future, but we develop everything internally, which takes time.

Q4: We use data for both early filtering and validation. I act as a ‘data scout,’ creating my own watch lists and sending players to scouting for final checks, or I review players found by scouts to see if they are a good fit based on data.

Q5: It's very difficult to guess what the future will look like because things change very fast. I believe AI will primarily be used to help the person decide and do that kind of work that it takes very long to do it. For instance, like Sevilla's system, AI can quickly search vast databases of scout reports to find players matching specific profiles, making people 'more efficient and to be quicker on their job.'

Q6: We have three things that are very difficult for us to handle in terms of data. Firstly, cost, accessing the best data is very expensive. Secondly, intangibles like the mentality and the psychological aspects of players, at the moment, we can't measure them, though scouts try to find news or assess performance in big games. Thirdly, the adaptation of a player after a transfer is very hard to predict, as personal issues can lead to mental breakdowns despite a seemingly perfect fit. These risks will always be there.

Q7: While the scouting department's opinion is still much higher than ours, our data-driven opinion is much more heard now than it was in the past. The Sports director makes the final call, considering inputs from the president, head coach, my data perspective, and the scouting department. Initially, there was cultural resistance to data, with people viewing me like a 'weird species.' However, by providing concrete proofs of data's value, it's become a core part of the club, to the point where it's impossible to live without data now.

Q8: The biggest barrier initially was cultural resistance. People are hesitant to adopt something they're not used to. However, this can be overcome with concrete proofs of data's worth. Other significant barriers include the very expensive cost of high-quality data and the current inability to measure intangibles like player mentality, psychological factors, and adaptation.

Q9: Yes, probably, I believe AI will fundamentally change things. It can be used literally everywhere in scouting and technical analysis, as well as broader club operations like predicting fan attendance or security needs. Things are changing rapidly; I expect significant differences even within a year, and I'm a big fan of AI, hoping it will be a 'big up for us.'

Q10: It's very difficult for me to answer that, but probably yes, because it could give smaller clubs tools they currently lack to compete. However, it requires a huge investment in tools and human resources that smaller clubs might not be able to afford. For example, some Portuguese clubs don't even have a scouting department, let alone a data department. I believe if all clubs have the same technology, bigger clubs will still have an advantage due to more and better people. So, I don't think it will change that much.

Q11: I would say 9 in 10 situations, the first ones that adopt will have an advantage. Early adopters gain an advantage by becoming ‘more comfortable’ and ‘more used to the technology,’ allowing them to really bring value and gain competitive advantage. It's almost impossible for a club starting now to reach our current level in a few months. While there's risk in early adoption, it's about finding the ‘right spot’ to jump on the train.

Q12: I think there will always be some difference because AI is a ‘huge monster,’ not a single software everyone uses. The bigger clubs will be more prepared and they will have more investment to back this challenge. For example, Manchester City might have 20 or 30 people working on this, making it impossible for clubs like ours to compete on that scale. This is just how the game and how the industry works.

Interview 12

Q2: Data scientists prepare the tools and the data, which is delivered to the scouting team or any other decision-maker. Then, they use the data alongside their knowledge and other tools to make their informed decisions.

Q3: Unfortunately, I can’t answer this due to privacy reasons.

Q5/Q8: It's just like in any field... Don't rely solely on data, but don't ignore it either. I think we should use it to our advantage as an extra tool or piece of information, knowing it's not enough in and of itself.

Q9/Q11: I do believe it. Provided that the models use the proper information and clubs and entities are able to create robust models, these can offer a huge advantage for the clubs using them. I don't think the advantage will diminish because I'm sure no two clubs will use the same model. Therefore, only the clubs with the best models will have the biggest advantage.