The 12th Player: Explainable Artificial Intelligence (XAI) in Football: Conceptualisation, Applications, Challenges and Future Directions

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Keywords: Explainable Artificial Intelligence, Machine Learning, Deep Learning, Football Analytics, Injury Prediction, Rehabilitation, Football Tactical Analysis, Human Factors, Human-Centred AI.

Abstract: Artificial intelligence (AI) has demonstrated tremendous progress in many domains, especially with the vast deployment of machine and deep learning. Recently, AI has been introduced to the sports domain including the football (soccer) industry with applications in injury prediction and tactical analysis. However, the fact remains that the more complex an AI model is, the less explainable it becomes. Its black-box nature makes it difficult for human operators to understand its results, interpret its decisions and ultimately trust the model itself. This problem is magnified when the decisions and results suggested by an AI model affect the functioning of complex and multi-layered systems and entities, with a football club being such an example. Explainable artificial intelligence (XAI) has emerged for making an AI model more explainable, understandable and interpretable, thus assisting the creation of human-centered AI models. This paper discusses how XAI could be applied in the football domain to benefit both the players and the club.

1 INTRODUCTION

During the last decade the advances in artificial intelligence (AI) have been significant to the world. Machine and deep learning (perhaps the most popular subsets of AI) have been integrated in numerous technology-enabled sectors (Russell, 2010) forming a vital part in their operations. Beyond the corporate sector, AI became a vital part in people's lives, improving their everyday tasks and quality of life. Examples include voice recognition, self-driving cars, and recommendation systems (Gupta et al., 2021), (Bharati et al., 2020a), (Mondal et al., 2021), (Bharati et al., 2020b). AI is also being deployed in the sports industry including football (Moustakidis et al., 2023). The main goal of utilising AI is to improve the decision making in numerous areas. Notable examples include improving individual players' and the team's performance and development (Moustakidis et al., 2023), assisting in scouting, identifying potential talents from the youth academies, enhancing analytics and tactics, predicting and potentially preventing injuries and optimising rehabilitation periods for injured players (Rathi et al., 2020).

The sophisticated learning, reasoning, and adaptation capabilities of AI models have proved to be pivotal in all of the areas it has been utilised, including the sports industry, and require little or no human intervention (Arrieta et al., 2020). However, the fact that machine and deep learning algorithms follow a black-box approach (Arrieta et al., 2020) presents challenges in explaining a model's decisions and predictions. AI models do not provide sufficient justification, explainability, and interpretability on their overall behaviour (Gunning et al., 2019). Evidently, clear and precise explanations are vital towards demystifying how AI operates, especially when deployed in complex and multi-layered domains such as football, where the decisions and predictions may affect a team's performance and even more importantly a player's health.

Gaining an in-depth understanding of how AI systems function and achieve their results is needed, especially when critical decisions need to be made (Goodman and Flaxman, 2017). In the sports industry, especially football, decisions are made on a daily basis with regards to multiple operations of a club, including scouting procedures, team tactics, opposition analysis, players' personal fitness/rehabilitation programmes and injury prevention procedures. Even a small miscalculation can be proven financially costly for the club. In addition, the players' physical and mental health and overall wellbeing can be negatively impacted. Therefore, there is need for improved ex-

Procopiou, A. and Piki, A.
The 12th Player: Explainable Artificial Intelligence (XAI) in Football: Conceptualisation, Applications, Challenges and Future Directions.
DOI: 10.5220/0012233800003587
In *Proceedings of the 11th International Conference on Sport Sciences Research and Technology Support (icSPORTS 2023)*, pages 213-220
ISBN: 978-989-758-673-6; ISSN: 2184-3201

plainability and interpreatability of AI models. Furthermore, there is need for human experts to reassure both themselves and relevant stakeholders that AI solutions are transparent, unbiased, and trustworthy, by essentially minimising its black-box nature (Miller, 2019). Explainable Artificial Intelligence (XAI) emerged to make AI systems' reasoning, outputs and overall results more understandable and clear to human experts (Chazette et al., 2021), (Köhl et al., 2019), (Langer et al., 2021b), (Páez, 2019).

Motivated by the eminent concerns and opportunities observed, we discuss how XAI could be utilised in the football industry, focusing in various operations impacting both the team and individual stakeholders (players, coaches, sports analysts, etc.). Firstly, we provide the necessary background knowledge discussing key concepts of XAI, including definitions, the characteristics an XAI model should exhibit, and how XAI could become more human-centred. Subsequently, we discuss in-depth how XAI could be utilised in various aspects of the football industry, including scouting, tactical analysis, player development and performance optimisation, injury prediction and prevention and finally, rehabilitation. We conclude by summarising our insights and provide future directions on XAI applied in the football industry.

2 RESEARCH BACKGROUND

2.1 XAI Definitions

Numerous definitions have been proposed to capture the meaning of XAI. The most notable ones define XAI, in general terms, as one of AI's sub-fields that is responsible for accompanying an AI model with intelligible explanations to the end users and stakeholders by constructing effective and accurate approaches (Van Lent et al., 2004) (Biran and Cotton, 2017), (Miller, 2019), (Mittelstadt et al., 2019). More specifically, XAI has been defined as the set of features that assist users understanding how an AI model constructs its predictions (Arrieta et al., 2020), (Nazar et al., 2021). To this end, XAI should highlight the most influential factors contributing to the prediction process (Viton et al., 2020), hence allowing more efficient pre-processing to be conducted.

Making an AI model more understandable and explainable does not directly guarantee its interpreatability, especially when it is used by multiple types of users with different levels of expertise and knowledge and varying degrees of experience. This issue was correctly raised by (Bharati et al., 2023). Specifically, it is argued that explainability focuses on the 'why' behind a decision and not on the 'how', while intepretability deals with making the users understand the rationale behind its decision (Vishwarupe et al., 2022), (Miller, 2019).

An important factor to consider when it comes to XAI is the need for reassuring the human experts/users that the AI model constructed is neither biased nor discriminating (Duell et al., 2021). XAI plays a pivotal role in strengthening trust between human experts and AI models and assisting in better collaboration between the two (Adadi and Berrada, 2018). In conclusion, the authors in (Gunning et al., 2019) effectively stated that XAI should be heavily influenced by the social sciences (Miller, 2019), specifically the psychology of explanation, and should aim to make machine and deep learning algorithms:

- More explainable and socially aware, while also maintaining their high levels of accuracy.
- Human-centred, by assisting in creating and maintaining trust between human experts and AI.

2.2 XAI Characteristics and Goals

According to (Arrieta et al., 2020), the main properties an XAI model include:

- ***Understandability (also called Intelligibility):*** An AI model should make its functioning and decision-making more understandable to humans. Low-level details such as its inner structure and algorithmic training procedure should be omitted.
- ***Comprehensibility:*** An AI model should provide human-readable explanations regarding its learnt knowledge. In that way, its complexity becomes more approachable to human operators.
- ***Interpretability:*** An AI model should describe results in a human-meaningful way.
- ***Explainability:*** An AI model should provide meaningful explanations about the results to assist human experts in their decisions.
- ***Transparency:*** An AI model should be fair, unbiased, and transparent without leaving any details or knowledge hidden, vague or ambiguous to human experts.

2.3 User-Centred XAI

The most important objective of XAI is to provide substantial support to the various types of users in accurate, effective and correct decision-making (Nadeem et al., 2022), thus demystifying AI's black-box nature. We proceed with discussing a set of common practices with which XAI can be realised in practice based on previous work by (Nadeem et al., 2022).

2.3.1 XAI Enabled by Visualisation

The construction of visualisations is the most popular and straightforward way of providing explainability and understandability of how an AI model operates. This is due to human cognition being in favour of visual information instead of text when it comes to decision making (Padilla et al., 2018). There are multiple parts of an AI model that can be visualised. One approach is to visualise how an AI model proceeds to make a decision. Visualisations work particularly well with tree-based machine learning algorithms such as decision trees and random forests (Angelini et al., 2017), (Sopan et al., 2018), (Nadeem et al., 2021). Other approaches include providing visual analytics regarding the data input, so that human experts can perform manual investigation in further (Angelini et al., 2017), or presenting additional visual information selectively based on the human expert's trust levels (Anjomshoae et al., 2019).

2.3.2 XAI Enabled by Usability Testing

When it comes to effective, accurate, and correct decision making by human experts, usability becomes a priority. Complex visualisations could overwhelm human experts rather than assisting them (Nadeem et al., 2022). Therefore, the explanations provided by an XAI model must be as clear, precise, and simplistic as possible so human experts can effectively and efficiently utilise them (Antwarg et al., 2021), (Panigutti et al., 2022). There is a also a need to eliminate the misconception that explainability automatically provides interpretability (Nadeem et al., 2022). Interpretability can improve decision making since it can identify bias in the training data and can also ensure that the variables involved meaningfully contribute to the results of the AI model (Arrieta et al., 2020).

Additionally, achieving understandability involves ensuring multiple usability factors that are evaluated through effective user testing (Doshi-Velez and Kim, 2017). Hence, it is essential for an XAI model to be user-centric and multiple rounds of user and usability testing to be conducted (Doshi-Velez and Kim, 2017). Sepcifically, before an XAI model is deployed on top of the AI system in place, in-depth usability testing must be conducted. In this way, enlightening feedback will be received from the users and all the necessary changes will be made. Essentially, an XAI model should be designed and evaluated based on the feedback from the users involved.

2.3.3 XAI Enabled by Different Stakeholders

The results generated by an AI model are essential for effective decision-making procedures by various types of stakeholders exhibiting different background knowledge, expertise, experience, needs, and motivates. Hence, each stakeholder will potentially require different understandability, comprehensibility, interpretability, explainability, and transparency approaches, tailored and adapted to their individual needs (Blumreiter et al., 2019).

3 XAI IN FOOTBALL

XAI aims to support in accurate, effective and correct decision making (Nadeem et al., 2022). In football industry, there are multiple types of users/stakeholders involved in order for a team to be fully functional. Examples include managers, assistant managers, fitness/conditioning coaches, chief sports analysts, nutritionists, physiotherapists, and scouters. Every user comes from a different scientific background, with different levels of experience and expertise, responsibilities and roles in the team. In practice, an XAI model should help each of these users understand how AI models were constructed, function, what the results reveal, and provide useful insights and conclusions about the input data it received, tailored to their needs, level of experience and knowledge (Nadeem et al., 2022). We proceed by discussing how XAI could be integrated in various football aspects, highlighting which of the characteristics and goals defined in the previous section are vital for its effective utilisation. Our guidelines and recommendations are also summarised in Table 1.

3.1 XAI in Scouting

Recruiting/scouting is one of the most important processes for football clubs. Most of the clubs have a combination of human scouting experts physically attending games and watching the potential players to be signed and also using AI tools to assess a potential player's suitability for the team.

Several stages in scouting can enhanced by AI. The first stage consists of the AI model identifying which positions in the team require new/additional players for maximised performance and effective player-rotating. The second stage is collecting the relevant data for accurate comparison between the players the team is interested in recruiting. This includes performance statistics for each player, such as passes (short/long/dangerous) completed, successful assists,

Table 1: Summary of XAI utilisation to the Football Industry.

Stakeholders	XAI Application in Football
Players	-Injury prediction and prevention -Personalised rehabilitation programmes -Personal training programme
Managers Assistant Managers	- Decision making at player and team level - Exploration of alternative tactics - Player position changes for improved team performance
Coaches Fitness/Training Experts	- Youth/Pro Players monitoring and development - Performance optimisation
Sports Analysts Chief Sports Analysts	-Tactical/Opposition analysis -Gameplay patterns
Nutritionists Physiotherapists Healthcare Specialists Medical Team	- Injury risk monitoring and Targeted interventions -Rehabilitation monitoring and adjustments -Wellbeing and fatigue level monitoring -Physical and mental health monitoring
Scouters	- Talent identification

on and off target shots, successful dribbles, successful aerial battles won, successful interceptions/tackles, successful saves (goalkeepers), and so on. The AI-informed scouting team can subsequently go and actually watch the players in-action to gather subjective evidence, beyond statistics (Ryan Beal and Ramchurn, 2019). Examples include but not limited to off-the-ball movement abilities, positioning, bravery in pursuing challenges, team responsibility, stamina, concentration, good communication and good reflexes. Once all the necessary data is gathered and based on the available budget, optimal decisions can be taken. This is essentially an AI-optimised problem, meaning getting the most highly-rated players with the least budget. There are also other factors to consider, such as squad sizes and player wage caps. As the literature suggest (Ryan Beal and Ramchurn, 2019), scouting is a process that can involve both human experts and AI models, each bringing their own skills in the formula.

XAI could assist in the scouting process by firstly identifying the best players for the required positions, why these players were selected and based on which factors (understandability and explainability), and how these factors contributed to their selection (interpretability). Moreover, the XAI model, based on the observations and feedback provided by the human experts (scouters), can visually quantify which players are the most suitable and why (understandability and explainability) and what requirements they satisfy (interpretability). Finally, XAI could suggest on alternative players, based on available budget.

3.2 XAI in Tactical Analysis

Unarguably, football is one of the most complex sports and one of the most challenging to analyse due to the large number of players involved and their varied roles. AI can model the behaviour of players and identify team gameplay patterns (Moustakidis et al., 2023), in an attempt to provide sufficient information on which players are the most influential on the pitch, the most reliable when it comes to goal scoring, the most successful in stopping counter-attacks, with the highest number of dangerous passes, and so on.

XAI could assist in explaining how different formations of the squad could contribute to the players'/team's improved performance (understandability), thus explaining why certain players perform better under certain circumstances (different position, opponent, cooperation) (explainability and comprehensability) and what factors (features) have contributed to it, as well as how these factors were handled from the AI model (interpretability). Moreover, based on what the manager and assistant managers would like to try out, XAI could be used to suggest alternative positions for certain players and different formations, where their performance is maximised. In addition, XAI could similarly used to analyse the opposition team. In that way, the manager and the assistant manager can gain valuable and insights on what they are up against and make improvements to their team and/or construct alternative strategies.

3.3 XAI in Player Development and Performance Optimisation

Football clubs around the world invest a lot on their youth academies. Therefore, the appropriate development of youth players is essential for becoming successful candidates for joining the first team squad. AI systems can assist and optimise this process in numerous stages. Firstly, AI can provide information on the players' performance both during practice and game days. Input data can be performance related (e.g., successful shots/assists, passes completed, tackles/interventions, etc.) or physical data captured from GPS vests (e.g., total distance, high intensity distance, sprint distance, top speeds, etc.) (Ryan Beal and Ramchurn, 2019). Moreover, AI can be vital in personalising the training programme for each footballer, according to their skills and capabilities and the needs of the team. AI could also assist in decisions relating to assigning a player to a higher level team or a smaller club for gaining more experience and playing minutes. More specifically, an AI model could map players (youth/professional) to specific strength/conditioning programmes based on their physical characteristics and objectives set by the coaching team. XAI could assist in visually quantifying the performance of players (understandability), thus explaining why a player is performing in a specific way (explainability and comprehensability) and what factors contributed, as well as how these factors were handled from the AI model (interpretability).

In this way, the "weak points" of a player can be identified allowing the personnel involved to take informed action. In case a footballer needs to become physically stronger, the strength and conditioning team can re-construct their fitness programme along with the nutritionist who can improve their diet plan. If the footballer needs to work on improving their technique and/or specific actions (e.g. passing accuracy), the manager/coaching personnel could use re-construct their individual practice programme, so they can improve. In addition, XAI could suggest alternative positions for certain players (especially youth players), based on their performance and physical characteristics (understandability, explainability and comprehensability) and how certain factors contribute to the alternative position (interpretability). Managers and assistants could use this information to improve their team tactics/strategies and rotation systems, coaches could differentiate their personal programmes, while the conditioning team could make the necessary changes to their exercise programme based on their role on the pitch.

3.4 XAI in Injury Prediction/Prevention

Injuries in football can be severe and many times season ending. Certain types of injuries may be avoided or at least their magnitude and impact may be significantly minimised. AI could be used as an injury prediction and prevention tool by monitoring the players' overall movement to identify poor body posture, incorrect form or overexertion, allowing potential risks of injury to be identified. The AI model could make insightful suggestions to readjust posture or to prevent an injury, such as specific exercise programmes to strengthen certain muscle groups. XAI could be used to identify the types of injuries each player is at risk of experiencing, visualising the factors contributing to this risk (understandability and explainability) and how these factors can impact the players' health and wellbeing (interpretability) through visual quantification of these risks. The results obtained can help the coaching and medical teams understand what adjustments need to be made and how, hence creating personalised exercise programmes to ensure the players' health, safety, and improved performance.

In addition, the game minutes could be analysed by the AI model, to estimate which players are potentially at risk of injuring themselves based on the number games played and their resting periods between games. Once again, the XAI model could provide accurate visualisations on the potential "fatigue" levels of the players and how these are constructed. Such results can assist the managers into constructing an optimised and safer player-rotation system.

3.5 XAI in Rehabilitation

Inevitably, most footballers will suffer from injuries during their career. Some of these injuries may be long-term and require one or more surgeries. Hence, proper rehabilitation is essential for effective recovery. Undeniably, every footballer is different and therefore, every injury in manifested differently. AI could assist in personalising the rehabilitation programme for each player based on the type and severity of injury, their biomechanics and how each player corresponds to the rehabilitation programme to maximise the probability of a successful recovery. In detail, the AI model could take a closer look to each player's biomechanics so it can spot any weaknesses or imbalances that may contribute to their slower rehabilitation. In addition, AI could estimate approximate recovery timelines based on the current progress made by the player as well as similar previous cases. Finally, AI could track players' movements in real-time and provide effective feedback to maximise their progress and minimise the risk of re-injury.

Through XAI, medical/healthcare specialists (sports injury rehabilitation, physiotherapy/conditioning team) can understand the purpose of a specific rehabilitation programme (understandability, explainability) and what factors contributed to its selection. Examples of important factors include the type/severity of injury, medical intervention (if any), whether it is a recurrent injury, player's biological characteristics (e.g., age, height, weight, BMI), biomechanics (e.g. muscle imbalances) and performance results (e.g., stamina levels). In addition, XAI could explain why certain movements put the player at risk of re-injury by visualising how they currently move and how they should move correctly to avoid putting additional physical stress to the injured area. XAI should also assist in presenting similar past cases (similar injuries/recovery) to illustrate common points between them and the current case to support its decision (Comprehensability). Interpretablity could provide more information on how these factors are used by AI and how influential and important they were when choosing the specific rehabilitation.

Additionally, managers and assistant managers can keep track of their players' progress and get an estimation on their possible return date. In addition, nutritionists could be informed though the XAI model on the players' current exercise programme and its physical requirements, so they could construct a corresponding diet plan based on their bodies needs. Finally, transparency should be considered so that every player is treated fairly with regards to their condition, receives clear instructions on what is required from them throughout the different stages of the rehabilitation programme and what improvements can be made from their side to maximise results.

4 CHALLENGES AND FUTURE DIRECTIONS

XAI is an interdisciplinary research field in the realm of AI (Brunotte et al., 2022),(Langer et al., 2021a),(Langer et al., 2021b). Hence, several challenges emerge when attempting to provide sufficient explanations on its functioning. Firstly, providing clear, precise, and sufficient explanations is more complex than it seems. It is essentially a sociological issue (Miller, 2019), which ultimately refers to the following question: *how can we evaluate the quality of an explanation?* (Longo et al., 2020). Ultimately, there is no single correct answer as it can have multifaceted implications for different stakeholders. Therefore, in-depth cognitive experiments should be conducted to decide on the presentation of explanations (Longo et al., 2020). This is demonstrated in the football case study presented, as multiple stakeholders are involved with different background knowledge, expertise, experience, motives, goals, and responsibilities. Therefore, what comprises an explainable set of information can vary for each stakeholder. A possible approach towards simplified and straightforward explainability would be to use abstractions (Gunning et al., 2019). In addition, an XAI model should be able to explain to human experts about not only its decisions but also its skills and capabilities (Gunning et al., 2019). Even the most sophisticated AI systems have their own blind spots and may have cases which they might not have the perfect answer. An XAI model should harmonically co-exist with human experts to develop cross-disciplinary insights and common baselines, helping both human experts and other AI agents learn, and improving their own knowledge by using past knowledge and experience to accelerate discovery. This re-emphasises the human aspects of AI.

Furthermore, one should consider the legal implications and the factor of accountability when it comes to XAI. If an XAI model provides an incorrect suggestion, what are the legal implications? Who is affected? What are the consequences? What are the socio-economical, health and safety implications? In addition, we should consider whether XAI explanations could negatively impact the safety and privacy of individuals (et. al., 2023). Some important questions to ask are: *How can XAI impact privacy and safety? Which human factors should be considered?* Such questions are especially important when sensitive information is involved. In the present case study, this may relate to the players' injuries records, performance and medical data. Even an accidental leakage, could lead to great consequences to individuals and teams. A possible countermeasure would be to anonymise data and partially release anonymised sensitive data as a baseline to collect more intelligence about the individuals involved (Cai et al., 2016).

Moreover, XAI should be human-centred to facilitate usable and beneficial interactions between human experts and AI (Amershi et al., 2019). Beyond the relevant HCI-related principles that should definitely be considered when designing an XAI-enabled interface, multiple iterations of user testing and usability studies should be conducted. In addition, important questions should be discussed before proceeding with designing the XAI-enabled interface (Bush et al., 1945), such as whether XAI should include additional explanations on particular users who may lack relevant knowledge, and how explanations can become more interactive to keep human users engaged while assisting them in understanding difficult concepts more efficiently. In the case study presented, it is clear that deploying a one-fit-for-all XAI system is not sufficient and that the approach should be differentiated based on the individual's knowledge, skills, experience and duties.

In addition, XAI should contribute towards more responsible AI. It is no secret that an AI system automates multiple and complex tasks simultaneously. Although its capabilities are remarkable with how fast and accurate considerable amounts of data can be handled, the fact remains that errors and miscalculations will be made. In such cases, it should be clear and precise on how such mistakes are handled, who is responsible to identify and respond to any mistakes, who should be held accountable (et. al., 2023).

5 CONCLUDING REMARKS

The effective and correct conceptualisation and utilisation of XAI is still a work in progress. This holds especially true for the football (soccer) sector, and the sports industry in general, as to the best of our knowledge no substantial research has been made for it yet. Hence, in this paper we aimed to discuss how XAI could be applied in various domains of a football club to benefit all the relevant stakeholders. In particular, we have discussed how XAI is defined and what its characteristics are and the need for XAI to be user-centred. We explored the domains of the football industry (focusing on the footballers-related procedures) where XAI can be utilised and how can this be beneficial for the diverse target groups involved.

Finally, since XAI is a relatively recent area of research, there is still plenty of improvement and work to be done. Hence, we discuss what challenges XAI faces, focusing on the case presented. In the future, it is essential for XAI experts to address these challenges so XAI can be deployed alongside AI. Without a doubt, XAI is going to be one of the most important components an AI system should possess. As the field of AI expands its application areas and obtains a more substantial social role, it is essential to remain in-sync to the needs of human users.

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