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Perspectives on data analytics for gaining a competitive advantage in football: computational approaches to tactics

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ABSTRACT

The role of data-driven analyses is becoming more prominent in football. These have the potential to impact decision-making processes for team performance and player recruitment. Research in this area makes use of large datasets consisting of event and tracking data from multiple teams, leagues and seasons. A well-known computational solution is the Expected Goal model for post-match analysis and operational decision-making.

Despite a shared research interest in football tactics, computational research in football is somewhat disconnected from the sports science community. We believe that there is much to gain from a closer collaboration between these disparate communities. To this end, the present commentary has three goals. First, we want to synthesize the historical computational work in areas such as evaluating tactics, predicting player and team success, and modeling players' movements. This work has largely been published in technical computational venues, and hence we hope to provide an access point for those interested in learning about this area. Second, we will highlight some emerging topics, such as automating parts of match analysis and analyzing decision-making. These are topics that require an in-depth collaboration with domain experts and therefore would benefit from a tighter integration among these communities. Third, we would like to discuss some advice and initiatives that we hope will be helpful in strengthening the ties between these communities.

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Soccer; soccer analytics; machine learning; artificial intelligence; football analytics

Introduction

Across multiple different sports, data-driven analyses are becoming increasingly common in providing solutions for athlete performance (Kubatko et al. 2007; Lopez 2020; Elitzur 2020; Goes et al. 2021; Brefeld et al. 2024; Davis et al. 2024). Colloquially, this trend is referred to as the 'Moneyball revolution' based on the name of the popular book by Michael Lewis that describes how data-driven decision-making was used for gaining competitive advantage in baseball (Lewis 2004). In practice, this is a catch-all phrase to denote how data-driven analyses inform team's performance evaluation, roster construction, and tactical decisions to enhance performance (Lolli et al. 2024).

Football (or soccer) is no exception in this regard. Although video analysis has become common practice for tactical analysis in football (McRobert et al., 2023), teams have been seeking further competitive advantage through computational methods (Power et al. 2018; Goes et al. 2021; Bauer and Anzer 2021). A well-known example is the expected goals (xG) metric (Lucey et al. 2015; Anzer and Bauer 2021), which has added value to operational decision-making in the transfers and recruitment of players (Graham 2024) but has also been referenced in post-match analyses by pundits and managers to describe team performance. Beyond xG, computational research has contributed to understanding football tactics in a variety of other ways, such as quantifying how players contribute to a team's performance (Kharrat et al. 2020; Pelechrinis and Winston 2021), automating analysis of individual player tendencies (Decroos and Davis 2019; Decroos et al. 2020), and modeling the movement patterns of teams as well as players (Spearman et al. 2017; Le et al. 2017). This research has produced insights that have been implemented and used in practice by clubs, federations and data providers (O'Hanlon et al. 2022; Graham 2024), which has been facilitated by an integration of data science in backroom staff (Windt et al. 2021).

Despite a shared interest in analyzing football tactics by computational and sport scientists, knowledge and

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skills on computational research mainly reside within the computational science community (e.g., AI, statistics, operations research). Moreover, collaboration with sport science is relatively limited, possibly due to different approaches to football tactics. Whereas computational researchers approach football tactics through the development of novel algorithmic tools and large datasets (Le et al. 2017; Bransen et al. 2019; Fernández and Bornn 2020; Dick et al. 2022), sport scientists aim to support tactical performance through collaboration with practitioners in evidence-based practice and (experimental) research designs (Fullagar et al. 2019; Goes et al. 2021). Because these communities employ different scientific tools and bring different perspectives, we believe that a tighter integration between them would yield a strong multi-disciplinary research approach to advance football analytics.

The purpose of this commentary article is to draw attention to how current and future advances in football analytics can be used for competitive advantage, with the aim of encouraging more collaboration between computational and sport scientists. More specifically, we aim to accomplish this goal in three ways. First, we aim to overview some of the historically prominent lines of computational research that have primarily been performed by researchers outside of the sports science community. Since these studies have appeared in a diverse set of literature including AI (Fernández et al. 2021), data mining (Decroos et al. 2019), and operations research (Kharrat et al. 2020), it can be difficult to have an overview of what exists, particularly for researchers interested in learning about this area. Second, we aim to highlight some emerging trends in computational research. The unifying theme is that these problems strongly benefit from, or even require, deeper integration of sports expertise (and indeed have often involved this (Shaw and Gopaladesikan 2021; Wang et al. 2024)). Third, we will discuss some guidance and activities about how such collaborations can be further promoted. Namely, we will provide some (anecdotal) advice, particularly with respect to possible pitfalls that may arise and how to avoid them. Moreover, we will describe what initiative may be necessary to drive the collaborations forward.

Computational methods in football

A characteristic of computational research in football is the focus on the analysis of large datasets involving multiple teams (c.f., Fernández and Bornn 2020; Anzer and Bauer 2021) and often multiple leagues (c.f., Decroos et al. 2019; Pappalardo et al. 2019; Liu et al. 2020). In some cases, they also contain a longitudinal component (c.f., Bransen and Van Haaren 2020; Kharrat et al. 2020; Robberechts and Davis 2020). Two types of data about football matches underlie these studies: event data and tracking data.

Event data record on-ball actions (e.g., passes, shots) and other relevant events in matches (e.g., cards, substitutions). Each event is described by a number of characteristics (e.g., location, type, players involved, timestamp). These data are typically manually annotated. Moreover, it only tracks on-ball actions, i.e., each annotation only records information about one of the 22 players on the pitch. Interestingly, there is a large amount of public event data (around 4,000 games) that can be used for non-commercial purposes (Pappalardo et al. 2019).[1] Historically, event data were difficult to obtain and were not shared publicly.

Tracking data is typically derived by applying computer vision techniques to video (Rahimian and Toka 2022). Although tracking data can also be obtained from wearable technology, such as Global or Local Positioning Systems (GPS or LPS, respectively), this is usually done on a smaller scale. Optical tracking data can be obtained from dedicated in-stadium installations or broadcast footage. These approaches record the geometrical coordination of all players and the ball multiple times per second (Shitrit et al. 2011, 2013). However, there is little publicly available tracking data.[2]

Given the increased access and availability of meaningful football data, either publicly or at football clubs and federations, data-driven research broadly focuses on various themes in football research: identifying and evaluating different tactics, designing performance indicators based on predictive models, and modeling player movement. This research appears predominantly in the computer science literature, such as peer-reviewed AI or data mining conferences or journals. This may pose a challenge for sport scientists who may not come across this literature. Therefore, we provide an overview of the prominent research lines to address the first aim of the article. When discussing them, we will focus less on the underlying methodological approaches and more on the problems that have been tackled. To align with the aims of the article, we emphasize solutions provided by Machine Learning (ML) techniques, which frame daily football questions as prediction problems.

Evaluating tactics

Many football teams have invested in the development of analytics departments (Windt et al. 2021; Lolli et al. 2024). This is facilitated by the accessibility of mainly event data by commercial parties and/or league-wide deals and investments in tracking technology. Club analysts use the data to explore effective tactics for the club's playing philosophy and style (Fernández and Bornn 2018). Although football is a complex sport with intermittent changeovers in ball possession, most analysts use a game model that accounts for in-possession, out-of-possession, transition phases, and set pieces (Hewitt et al. 2016). By investing in data science skills and utilising computational techniques, clubs hope to gain a competitive advantage from data-driven insights (Lolli et al. 2024).

Teams' playing styles often incorporate agreements on where and how to press the opponent when out of possession (Andrienko et al. 2019). A quick regain of ball possession allows for control over the ball and entering the build-up phase. Bauer and Anzer (2021) developed a rule-based approach to identify counterpressing situations using a mix of event and tracking data. They evaluated counterpressing by determining the duration of regaining ball possession and the success of ball regain (i.e., shot on target). Also, Merckx et al. (2021) evaluated the effectiveness of pressing using a risk-reward framework. The risk arises from a team leaving its shape to press, which opens up space if the press is broken. The reward is the chance that the team can regain the ball. This can be useful for teams who have not been effective in pressing and seek ways to enhance their pressing style.

Corner kicks have also been studied in football analytics (Power et al. 2018; Shaw and Gopaladesikan 2021; Bauer et al. 2022). Both event data and tracking data seem useful to address tactical questions around set pieces. To illustrate, Power et al. (2018) used a combination of tracking and event data to understand the efficacy of in-swinging vs. out-swinging corner kicks and zonal vs. man marking schemes among other questions.

The aforementioned computational approaches evaluate football tactics for the different phases in the game, whether in or out of possession or set pieces. Beyond this, studies have examined tactical concepts, such as optimal timing to substitute players (Hirotsu and Wright 2002), where to place throw-ins (Epasinghege Dona and Swartz 2024), and the benefits of crossing (Wu et al. 2021).

Measuring player and team success

Evaluating individual and team performance through metrics derived from predictive models have become more important in daily football analytics. A popular example is the use of the xG model to evaluate the team's success in creating goal scoring opportunities. xG models can be based on either tracking data (Lucey et al. 2015; Anzer and Bauer 2021) or event data (Robberechts and Davis 2020). Given the characteristics of a shot, such as the shooter's position, whether it was preceded by an assist, and the position of the goalkeeper at the time of the shot, the model returns an estimated probability of the shot being converted into a goal. xG has proven to be useful in evaluating team's success on creating goal scoring opportunities and tends to be more predictive of future success than looking at goals scored (Anzer and Bauer 2021). It can also help to understand the player performance, both for goalkeepers (Yam 2019) and field players. One claim is that xG is often more stable than goal scoring rates for players. To our knowledge, this has also been explored in blogs (Elhabr 2023) and not in scientific publications. While there is a lack of peer-reviewed evidence demonstrating that xG is more stable than actual goal scoring rates, this does not diminish its value as a useful indicator of a player's performance. This model has been used in clubs' processes in player recruitment, transfers, and team evaluation (Graham 2024).

Predictive modeling has been used to quantify player performance beyond just considering goal-scoring opportunities. Expected possession value (EPV) models adopt a broader perspective by evaluating the contribution of individual players to ball possession and overall team success. While some frameworks just focus on actions that progress the ball (i.e., passes or carries) (Rudd 2011; Singh 2019), most consider all on-ball actions (e.g., shots, tackles, clearances) (Decroos et al. 2019). These models evaluate actions based on how they alter the near-term chance of scoring based on the intuition that useful actions increase (decrease) your team's chance of scoring (conceding). Initially, approaches such as expected threat (xT) (Rudd 2011; Singh 2019) rated actions solely based on how they affected a team's probability of scoring (see Figure 1). However, more recent approach also considers the risk of losing the ball, and hence also assess whether an

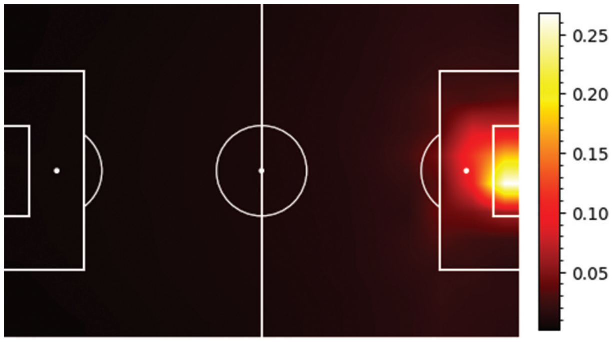

Figure 1. xT shows the probability that a team will score prior to losing possession for each location on a pitch. The image comes from https://github.com/ML-KULeuven/socceraction.

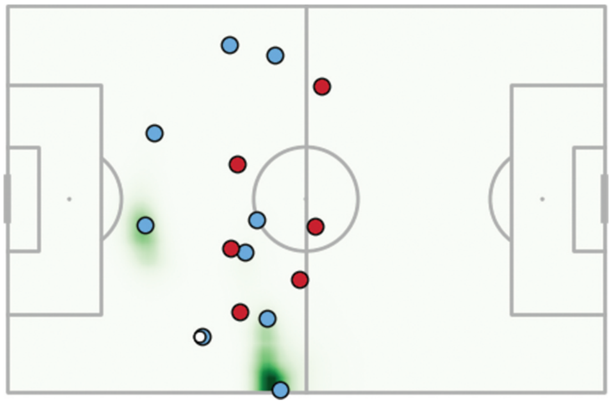

Figure 2. A pass selection surface that shows the most likely end locations for a pass in the current game situation. The blue team currently possesses the ball, which is represented by the white circle. The dark green regions represent the most likely locations for a pass. These surfaces play a key role in number of metrics, including Fernandez et al.'s possession value framework (Fernández et al. 2021) and Robberechts et al.'s creativity metric (Robberechts et al. 2023).

action decreases a team's probability of conceding (Decroos et al. 2019). Conceptually, EPV is derived from machine learned models. Specifically, given a game situation, these models are trained to predict the probability of scoring and conceding within a fixed time frame such as the next 10 actions or 10 seconds (Decroos et al. 2019; Fernández et al. 2021) (sometimes other objectives are used, such as reaching a certain zone on the pitch (Dick and Brefeld 2019)). A key differentiator among the existing approaches is how they represent the game situation. When using event data, approaches range from just considering the current location of the ball (Singh 2019; Van Roy et al. 2020) to considering a richer set of features such as information about previous actions (i.e., type and location), the current possession sequence (i.e., how quickly the ball is moving up the pitch), and contextual features (i.e., time remaining, score difference) (Decroos et al. 2019; Liu et al. 2020). When using tracking data (Fernández et al. 2021), the game situation considers spatiotemporal features of players, the ball, and the goals (Fernández and Bornn 2020). Many data providers offer their own event data-based EPV models (Statsbomb 2021; Statsperform).

A side-step from xG and EPV models is characterizing various aspects of passing behavior (Szczepański et al. 2016; Goes et al. 2019). This can entail evaluating aspects such as risk-taking (Power et al. 2017) (i.e., does a player systematically attempt passes that have a low chance of being completed), decision-making (i.e., what may have happened if a different pass was attempted) (Rahimian et al. 2022), passing creativeness (i.e., by analyzing which passes a player tends to select in a game situation; see Figure 2) (Robberechts et al. 2023), and the ability of players to make themselves available to receive a pass (Dick et al. 2022).

Modeling player movement

Tracking data is useful for understanding players' movements on the pitch and for modeling future movement behavior. There are two prominent lines of work in this regard: pitch control (Taki et al. 1996) and ghosting.

A pitch control model predicts the likelihood of a player reaching a given location before their opponent based on players' movement trajectories. Pitch control indicates the probability that a team controls an area on the pitch as illustrated in Figure 3. From the perspective of the team possessing the ball, the zones they control are considered safe options to pass the ball into. This probability is computed by considering a player's current movements (e.g., acceleration and/or velocity) over past couple of frames. These models can either be based on domain knowledge, such as physics (Spearman et al. 2017; Spearman 2018), or a combination of knowledge and learning (Brefeld et al. 2019). The models can also be weighted to account for the assumption that certain areas of the pitch are more valuable than others (Fernández and Bornn 2018). However, current models do not take individual characteristics into account (e.g., differentiating players based on their maximum speed). These approaches have the advantage of being extremely easy to visualize and interpret.

Ghosting is the popular name given to approaches that use tracking data to model players' future movements on the pitch (Lowe 2013). Specifically, historical information on player's location from a previous period (i.e., past seconds) is used to train models to predict a player's future trajectory (Le et al. 2017; Yeh et al. 2019; Rudolph and Brefeld 2022). Ghosting enables a comparison between the team's actual (i.e., observed) strategy and the team's planned strategy as designed by the coaching staff for that given situation (Le et al. 2017). An illustrative application is evaluating a team's expected defensive strategy in a certain situation, such as a counterattack, versus how they actually executed the defensive situation on the pitch. Based on the current and previous positions of the defenders, ghosting would provide insight into where they actually move and how they were supposed to move given the defensive strategy. Eventually, this can be evaluated on how the defenders' decision-making would affect the chances of conceding a goal. Although exemplar applications in football are currently scarce, basketball teams have integrated ghosting into performance analysis.

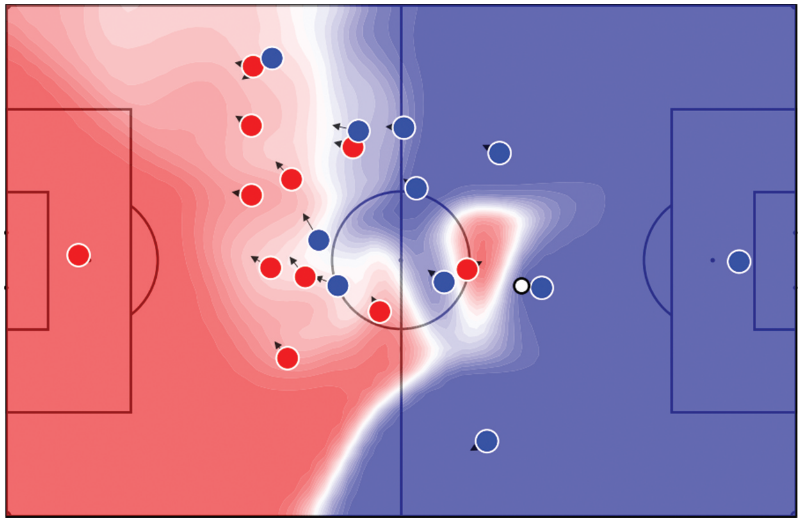

Figure 3. Illustration of Spearman's pitch control model. Darker red (blue) indicates that the red (blue) team exerts more control over that pitch location.

Emerging topics

More recently, computational advances are starting to be driven more by football-specific questions or targeting solutions aimed at supporting practitioners. For example, they may yield better ways to interact or search through data, result in time savings, or provide additional contextual insights into the validity of computational solutions (e.g., metrics derived from learned models). In this section, we highlight several of these trends and discuss the implications from a competitive perspective.

Automating analysis

Analysts are concerned with watching and annotating video footage typically using coding software (McRobert et al., 2023). Actions are visually evaluated on an individual or team-level during open play and set pieces, which is a tedious and time-consuming process and can involve errors due to the human nature of the observation (O'Donoghue et al. 2019). Computational approaches have the potential to automate some of the analysis, which may allow for a quicker and more accurate (e.g., by reducing perceptual errors) analysis. Research in this area requires access to tracking data. Initial work focused on identifying team formations (Bialkowski et al. 2014), and this has advanced to more recent work that explored how teams' formations vary over the course of a match, particularly in relation to the phase of play (e.g., build up, attacking) (Bauer et al. 2023). Moreover, these phases of play were automatically detected by a learned model.

Computational research has also explored automatic pattern detection during set pieces, and corner kicks in specific. Shaw and Gopaladesikan (2021) used tracking data to identify team-specific commonly occurring movement patterns. Specifically, they identified trajectories of offensive players represented as the start and end positions of players. Additionally, analysts are interested in understanding the roles that players take on, such as whether a player is performing player or zonal marking, when analyzing corner kicks. Bauer et al. (2022) focused on automatically assigning one of the seven different hand-defined roles to defensive players based on their observed behavior. These roles correspond to defensive types (e.g., player marking, zonal marking, backspaced defender) and were developed based on expert domain knowledge. The advancements of automatic detection of players' trajectories and roles during corner kicks can be useful for coaches and sport scientists in determining effective corner kick variations against different defensive strategies, minimizing the chance of conceding a goal from a corner kick by changing the defensive set-up, and model which corner kick variations result in shots on goal.

Automatic detection of patterns is also possible during open play. Instead of an analyst having to search through video footage to identify clips with specific movement patterns, such as overlapping runs, it is possible to train models to automatically identify these (Anzer et al. 2022; Seebacher et al. 2023). Typically, the domain expert provides some example clips containing the pattern of interest (with the corresponding tracking data), which is followed by an iterative and interactive process of: 1) training a model to identify these situations and 2)acquiring new labels in a targeted way by asking the analyst whether or not certain clips contain the movement pattern of interest. This process relies on the domain knowledge of both the computational analyst to train such models and the video analyst to select the relevant football situations.

In summary, from a competitive point of view, such tools may enable teams to analyze a larger number of historical games from an upcoming opponent. However, training such models requires input from sport scientists (e.g., to define roles, provide movement patterns of interest). This is an iterative and interactive process between computational and sport researchers: where the feedback from domain experts helps refine the trained models to improve their performance. Moreover, by partially automating some tasks currently done by hand, video analysts can use the saved time on the quality control of the analysis, providing detailed feedback to coaches and players, and addressing tactical questions from the coaching staff.

Evaluating decision-making

Currently, several models exist to value the player's action, but not evaluate player's decision-making (on the ball). For example, EPV models give fine-grained estimates of the value of each action, but these estimates fail to capture decision-making. A player's EPV may have decreased after an action because the model valued the outcome as detrimental for the team's opportunity to create a goal-scoring action or advancing up the pitch. However, the chosen action may have been the best solution out of a range of bad options. It is therefore important to understand all the afforded actions to a player in that given game state (Bransen et al. 2019; Rahimian et al. 2022, 2024). Furthermore, there is a challenge in giving value to the outcome of the selected action: rewarding a player for making a bad choice which turns out to contribute to the team's success versus penalizing a player for making a good choice but not being able to execute it successfully. This has also been expanded to consider the effect of players systematically performing different actions in certain situations. For example, this can allow reasoning about the effect of shooting more or less often from specific pitch locations on the expected number of goals that a team may score (Van Roy et al. 2021, 2023).

There is also some emerging work on evaluating a player's off the ball movements (Stein et al. 2019; Peralta Alguacil et al. 2020). Peralta Alguacil et al. (2020) used computational models for off-ball movements during attack. In particular, the model evaluated how players' movements contributed to successfully receiving a pass by the player or a team member, the impact of the players' movements into dangerous areas on the pitch, and the contribution to pitch control. Furthermore, Peralta Alguacil et al. (2020) also described how their model was used in coaching interventions for a first division club. Specifically, they presented match situations to players where a model had assessed a player's choice about a selected pass and its related chance of success and (expected) impact. Moreover, they discussed how the model suggested several off-ball positioning adjustments that the coaching staff strongly agreed with. Although this is an uncontrolled intervention in a case study, it highlights how insights from computational models can be used in discussion with coaches and players about on-pitch decision-making and tactical adjustments. However, it is crucial that such findings can be presented to coaches and players in an understandable manner.

Generative AI

The goal of generative AI or GenAI is to learn models that can produce data as their output. Currently, most work on this topic has focused on generating tracking data. For example, a collaboration between Google DeepMind and Liverpool FC trained a model using tracking data to synthesize player trajectories for corner kick routines (Wang et al. 2024). This resulted in generated corner kicks tactics that human analysts could not distinguish from real corner kicks.

Another example of GenAI relates to the generation of tracking data. Currently, tracking data derived from broadcast footage only records the locations of the players captured in the camera frame. In this case, GenAI has been explored as a means to generate the positions of the players that are not visible in the broadcast video (Omidshafiei et al. 2022; Hughes et al. 2024).

More speculatively, some products exist[3] that use GenAI to synthesize scouting reports. Though we are not aware of any peer-reviewed research on this topic.

Trustworthy AI

It is increasingly agreed upon that just optimizing predictive performance is insufficient to justify deployment of machine-learned models. Importantly, AI solutions have to adhere to (legal) regulations (e.g., GDPR, fairness). Whether a model satisfies such properties cannot be measured using standard aggregate evaluation metrics (e.g., accuracy, mean-squared error, ROC analysis, effect sizes). Instead, this requires alternative approaches to evaluation (Davis et al. 2024) and model building that consider factors related to trust, such as interpretability, fairness, and transparency (Straccia and

Pratesi 2022). In the pursuit of gaining competitive advantage, it is tempting to collect more data to train better models. However, not only does this warrant careful consideration of athletes' rights (West et al. 2024), it can also be argued that such models only provide a competitive advantage if the solutions are considered to be meaningful, actionable, and interpretable (West et al. 2024) by the coaching staff.

Interpretability

This refers to the ability to understand why models make certain predictions, and its importance is highlighted by Hecksteden et al.'s (2025) complementary article in the current issue with a working example. Interpretability can be considered in many ways, and computational techniques can be applied a priori or post-hoc to increase interpretability. Ultimately, it addresses a common criticism that AI models act as a so-called 'black box'.

First, it is possible to consider interpretability from the start, which typically entails two aspects. On the one hand, it is important to focus on using features that domain experts can understand (e.g., commonly used metrics in football tactics (Fernandez-Navarro et al. 2016) or locations on the pitch (Van Haaren 2021)). On the other hand, it requires using model classes that facilitate providing insights into a model's decision-making process (Caruana et al. 2015; Nori et al. 2019). This level of transparency in the modeling process helps improve the trustworthiness of the computational approach and ultimately in aids in delivering actionable solutions.

Second, it is possible to perform post-hoc analyses of (black box) models. These can be used to explain why a certain prediction has been made or gain insight into the overall working of a model. In the context of explanations, this often entails trying to identify which features are responsible for an individual prediction. A canonical algorithm for this is SHAP (Lundberg and Lee 2017). For a given example, it assesses each feature's importance by using a game-theoretic approach that assigns a value representing how much that feature contributed to the model's prediction. This has been explored in the context of xG (Anzer and Bauer 2021), which allows football experts to gain insights into why a model makes a specific decision or prediction. Alternatively, techniques exist to extract interpretable models from black box ones. This typically involves training a simpler model (e.g., single decision tree or logistic regression model) to mimic the behavior of the black box model (Craven and Shavlik 1994; Biecek 2018). This can be done at a global level (e.g., to extract knowledge (Craven and Shavlik 1995)) or a local level (e.g., to explain a prediction (Ribeiro et al. 2016)). For example, this has been used to understand which factors contribute to the value of an action in possession value models (Sun et al. 2020). Post-hoc analyses are important tools for helping experts assess what the models have actually learned and whether it agrees with domain knowledge.

Fairness

This typically entails investigating whether models are systematically biased or discriminate against certain groups defined by sensitive attributes, such as ethnicity or gender (Barocas et al. 2023). For example, race and gender seem to affect how people perceive the quality and certain characteristics of soccer players (Gregory et al. 2021). Consequently, if models are trained based on these annotations, they can perpetuate this bias. Another example that further highlights the importance of fairness is that xG has also been used to assess finishing skill by looking a player's 'goals above expectation'. This is computed as the difference between the number of goals a player has scored and their cumulative xG (Pleuler 2014; Baron et al. 2024). However, there is evidence that this metric is biased against good finishers by underestimating their skill level (Davis and Robberechts 2024). Such biases can undermine the validity of the metrics and hence call into question their suitable for use in practice.

Transparency

What constitutes transparency in AI is an open question, but current research focuses on issues such as providing (meta) information about data collection (Gebru et al. 2021) and model building (Mitchell et al. 2019). Such issues are clearly relevant for football data as design choices (e.g., considered data and feature sets) can impact performance (Robberechts and Davis 2020). Moreover, there are also open questions about how transferable models are across leagues. For example, xG models may be trained on shots from male top-elite football leagues, such as the Premier League and La Liga. However, these models may not be valid when they are applied to women's leagues (Bransen and Davis 2021; Narayanan and Pifer 2024) or lower-level male competitions because of differing league characteristics.

Advancing collaboration between sport and computational scientists

Our third aim is to promote collaboration between the computational and sport science communities. We believe that there is tremendous potential in this multidisciplinary collaboration, which seems to be an appropriate timing as computational approaches are moving closer to practice. Hence, this movement will benefit from a synergistic approach that incorporates the domain expertise of sports scientists. Simultaneously, sport scientists try to address questions that require appropriate computational approaches. In both situations, communities can benefit from each other's skills and domain knowledge. On the one hand, sports science can provide a rich set of real-world problems that can serve to illustrate failure cases of existing approaches and motivate the development of novel methodological approaches. Moreover, the sport expertise is necessary to ensure that developed models are relevant and yield actionable outcomes relevant to players, coaches and support staff, and football organizations. On the other hand, the proliferation of open-source and easy-to-use computational packages poses a risk: they may be used incorrectly. One may need deeper expertise to understand the technical conditions of when an approach is (not) applicable. Therefore, a collaboration between sport and computational scientists is recommended to ensure the correct application, adaptation, and interpretation of these methods to sport scientific problems. In pursuit of this goal, we will relate some personal 'lessons learned' from past collaborations and describe some initiatives that would bring the disciplines together.

Anatomy of a collaboration

When starting a collaboration, anecdotally there are several factors that are important to think about.

First, it is important to begin with a good question that addresses a relevant problem from the coaching, medical, or support staff. Often, such question can arise from specific sport scientific principles. It is important to keep in mind that computational researchers will lack domain expertise in sports to distinguish relevant from irrelevant information. An abstract or unguided question (e.g., 'Can AI solve my problem?') runs the risk of producing a result that is not interesting, practical, or useful for the sports context. A smooth running collaboration typically starts when 1) this question can be naturally mapped to the typical problem setting of interest to computational researchers, such as prediction, decision-making, knowledge/pattern discovery, planning or scheduling, and 2) there is a continuous conversation to ensure there is mutual understanding of the sport scientific and computational requirements needed to address the question.

Second, at the risk of being obvious: computational research requires access to data. It is hereby important to detail the quality and amount of available data as well as whether data sharing is possible (West et al. 2024). Most computational papers analyze existing and relatively clean data. Hence, computational scientists are much less familiar with data collection and the practicalities of cleaning noisy and missing data. It can help to highlight any quality issues or domain-specific data processing that may be needed.

Third, there should be a mutual agreement to try to understand the other domain. One should expect the computational researcher to invest some time in understanding the problem basis from a sport science perspective (and it is important to realize that this does take time). Similarly, it is helpful for sports scientists to familiarize themselves with some of the terminology used by computational researchers. For example, a sports scientist may use the term key performance indicator, whereas a machine learner would use the term feature.

Fourth, it is worth discussing the publication plans in advance. On the one hand, computational research is primarily concerned with methodological innovations. Hence, these papers focus on describing novel statistical models or machine learning algorithms and discussing any relevant mathematical results (e.g., proving that the algorithm satisfies certain properties). The results sections would then focus on comparing the empirical of the proposed approach to various competitors (e.g., evaluating their predictive performance on a large suite of benchmark problems). On the other hand, sport scientific research has the ultimate goal of supporting players and coaches by translating research knowledge and insights into practice (Coutts 2017; Bartlett and Drust 2021). Thus, the research combines a strong theoretical basis with an evidence-based approach involving key stakeholders to identify and address relevant questions from athletes, coaches, and support staff (Coutts 2017; Fullagar et al. 2019). Consequently, applying existing algorithms to solve a domain-specific problem is often considered out-of-scope for computational venues, whereas papers describing methodological advances motivated by sports data are not relevant to sports scientists. Differences in publication cultures further complicate this issue. Unlike sports science (and most other disciplines), computer scientists almost exclusively publish in rigorously peer-reviewed conferences. Hence, publications may 'count' or be valued differently in each domain. However, a collaborative effort could logically result in two publications. To illustrate, a common situation is that methodological innovations are required to address the sport-scientific problem. Therefore, one publication outlines the existing computational approaches and describes the technical advances that were made. Such a publication would most naturally target the computational community. The other publication would focus on contextualizing the work from a sports science perspective and contain a detailed analysis of the results (e.g., tactics, recruitment, and training program design). Moreover, it would highlight the relevant implications for using the results in practice.

Moving forward

We would like to highlight two types of initiatives that may help spur collaboration and further integrate these communities: joint events and open science.

First, we would make a plea to (continue) organizing joint events as we believe the benefits are two-fold. On the one hand, literally putting sport and computational scientists in the same room can help people meet each other and spur collaborations. Several of such initiatives have been organized in the past. For example, Dagstuhl Seminars have focused on bridging the gap between these areas (Brefeld et al. 2021). Some concrete outcomes include a curated and searchable list of venues where sport-related work is often published[4] and collaboration on the current commentary. Another example is the multi-disciplinary session on Match Analysis and Small-Sided Games at the World Congress on Science and Football.[5] On the other hand, such events provide the opportunity to disseminate research and may help alleviate some the aforementioned challenges with publishing. However, these happen infrequently, may be small in size (e.g., Dagstuhl seminars involve ~40 participants), and as of yet do not have an associated publishing mechanism.

Second, shared data platforms and open science initiatives can fast track the development of computational methods in football. Open-source packages are available for working with event and tracking data, which often contain permissive licenses (i.e., the code can be used commercially with no restrictions). For example, there are packages for xG (Robberechts and Davis 2020), possession value models (Decroos et al. 2019), and general packages for working with tracking data, such as Floodlight (Raabe et al. 2022) and Kloppy.[6] More generally, PySport aims to promote open-source sport software.[7] Moreover, this has the added benefit of reducing the barrier to entry and facilitates repeating analysis on new datasets. To help mitigate the potential for misuse, it is incumbent on researchers releasing such packages to provide clear instructions and guidelines about how to use them and when they are (not) applicable. Ideally, this should be done in combination with sports experts to ensure that the provided documentation is accessible to those with a non-computational background and supports valid application in practice. The fact that best practices from a computational perspective can change quickly further underscores the need for collaboration between computational and sport scientists, both to ensure that the guidelines are appropriately outlined for the intended audience and to promote the appropriate and up-to-date use of computational methods in sport science research.

Conclusion

This commentary aimed to provide an overview of current and emerging topics in football analytics and encourage collaboration between sport and computational scientists. We believe that there is tremendous potential to be gained through a tighter collaboration between the computational and sport science communities, but this may suffer from a limited view on what exists in computational research. Given that academic work in this area is primarily done by and shared with researchers working in artificial intelligence (AI), statistics and operations research, our first aim was to overview the historically important topics. Hopefully, by collecting some of the key ideas in one place, this article creates an entry point for sports scientists interested in learning about this area. Our second aim was to highlight some emerging trends within computational approaches to football. Our thesis was that these topics often require significant domain expertise and hence would strongly benefit from a tighter integration of computational and sport science. The third aim of the manuscript was to provide guidance and initiatives for fruitful collaboration between sport and computational scientists. Key factors are continuous communication, willingness to understand each other's domain knowledge, and joint events and open science. We hope that this commentary will spur further multi-disciplinary advances in this area.

Notes

1. https://github.com/statsbomb/open-data.
2. https://github.com/metrica-sports/sample-data. or https://www.blog.fc.pff.com/blog/pff-fc-release-2022-world-cup-data.
3. https://twelve.football/blog/combining-scout-reports-with-data-using-large-language-models.
4. https://dtai.cs.kuleuven.be/sports/venues/.
5. https://wcsf2023.com/programandbookofabstracts/.
6. https://kloppy.pysport.org/.
7. https://pysport.org/.

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References

Andrienko G, Andrienko N, Anzer G, Bauer P, Budziak G, Fuchs G, Hecker D, Weber H, Wrobel S. 2019. Constructing spaces and times for tactical analysis in football. IEEE Trans Visual Comput Graphics. 27(4):2280–2297. doi: 10.1109/TVCG.2019.2952129.

Anzer G, Bauer P. 2021. A goal scoring probability model for shots based on synchronized positional and event data in football (soccer). Front Sports Act Living. 3. doi: 10.3389/fspor.2021.624475.

Anzer G, Brefeld U, Bauer P, Fassmeyer D. 2022. Detection of tactical patterns using semi- supervised graph neural networks. Proceedings of the MIT Sloan Sports Analytics Conference. Boston, MA, USA.

Barocas S, Hardt M, Narayanan A. 2023. Fairness and Machine learning. Cambridge, MA, USA: MIT Press.

Baron E, Sandholtz N, Pleuler D, Chan TCY. 2024. Miss it like Messi: extracting value from off-target shots in soccer. J Quant Anal Sports. 20(1):37–50. doi: 10.1515/jqas-2022-0107.

Bartlett JD, Drust B. 2021.A framework for effective knowledge translation and performance delivery of sport scientists in professional sport. Eur J Sport Sci. 21(11):1579–1587. doi: 10.1080/17461391.2020.1842511.

Bauer P, Anzer G. 2021. Data-driven detection of counterpressing in professional football. Data Min Knowl Discov. 35 (5):2009–2049. doi: 10.1007/s10618-021-00763-7.

Bauer P, Anzer G, Shaw L. 2023. Putting team formations in association football into context. J Sports Anal. 9(1):39–59. doi: 10.3233/JSA-220620.

Bauer P, Anzer G, Smith JW. 2022. Individual role classification for players defending corners in football (soccer): categorisation of the defensive role for each player in a corner kick using positional data. J Quant Anal Sports. 18(2):147–160. doi: 10.1515/jqas-2022-0003.

Bialkowski A, Lucey P, Carr P, Yue Y, Sridharan S, Matthews I. 2014. Large-scale analysis of soccer matches using spatiotemporal tracking data. Proceedings of the IEEE International Conference on Data Mining. Shenzhen, China p. 725–730.

Biecek P. 2018. Dalex: explainers for complex predictive models in R. J Mach Learn Res. 19(84):1–5.

Bransen L, Davis J. 2021. Women's football analyzed: interpretable expected goals models for women. Proceedings of the AI for Sports Analytics (AISA) Workshop. Virtual event.

Bransen L, Robberechts P, Van Haaren J, Davis J. 2019. Choke or shine? Quantifying soccer players' abilities to perform under mental pressure. *Proceedings of the MIT Sloan Sports Analytics Conference*. Boston, MA, USA.

Bransen L, Van Haaren J. 2020. Player chemistry: striving for a perfectly balanced soccer team. *Proceedings of MIT Sloan Sports Analytics Conference*. Boston, MA, USA.

Brefeld U, Davis J, De Jong L, Kovalchik S. 2024. Computational approaches to strategy and tactics in Sports (Dagstuhl Seminar 24081). Dagstuhl Rep. 14(2):164–181.

Brefeld U, Davis J, Lames M, Little JJ. 2021. Machine learning in sports (Dagstuhl Seminar 21411). Dagstuhl Rep. 11(9):45–63.

Brefeld U, Lasek J, Mair S. 2019. Probabilistic movement models and zones of control. Mach Learn. 108(1):127–147. doi: 10.1007/s10994-018-5725-1.

Caruana R, Lou Y, Gehrke J, Koch P, Sturm M, Elhadad N. 2015. Intelligible models for health-care: predicting pneumonia risk and hospital 30-day readmission. *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. Sydney, NSW, Australia p. 1721–1730.

Coutts AJ. 2017. Challenges in developing evidence-based practice in high-performance sport. Int J Sport Physiol. 12 (6):717–718. doi: 10.1123/IJSPP.2017-0455.

Craven M, Shavlik J. 1995. Extracting tree-structured representations of trained networks Proceedings of the 9th International Conference on Neural Information Processing Systems. Denver, CO, USA. 24–30.

Craven MW, Shavlik JW. 1994. Using sampling and queries to extract rules from trained neural networks. *Proceedings of the 11th International Conference on Machine Learning*. New Brunswick, NJ, USA p. 37–45.

Davis J, Bransen L, Devos L, Jaspers A, Meert W, Robberechts P, Van Haaren J, Roy M. 2024. M. Methodology and evaluation in sports analytics: challenges, approaches, and lessons learned. Mach Learn. 113, 9 (9):6977–7010. doi: 10.1007/s10994-024-06585-0.

Davis J, Robberechts P 2024. Biases in expected goals models confound finishing ability. https://arxiv.org/abs/2401.09940 .

Decroos T, Bransen L, Van Haaren J, Davis J. 2019. Actions speak louder than goals: valuing player actions in soccer. *Proceedings of 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. Anchorage, AK, USA p. 1851–1861.

Decroos T, Davis J. 2019. Player vectors: characterizing soccer players' playing style from match event streams. *Proceedings of the 2019 Joint European Conference on Machine Learning and Knowledge Discovery in Databases*. Würzburg, Germany, Springer. p. 569–584.

Decroos T, Van Roy M, Davis J. 2020. Soccermix: representing soccer actions with mixture models. *Proceedings of the Joint European Conference on Machine Learning and Knowledge Discovery in Databases*. Ghent, Belgium, Springer. p. 459–474.

Dick U, Brefeld U. 2019. Learning to rate player positioning in soccer. Big Data. 7(1):71–82. doi: 10.1089/big.2018.0054.

Dick U, Link D, Brefeld U. 2022. Who can receive the pass? A computational model for quantifying availability in soccer. Data Min Knowl Discov. 36(3):987–1014. doi: 10.1007/s10618-022-00827-2.

Elhabr T. 2023. Meta-analytics for soccer https://tonyelhabr.rbind.io/posts/soccer-meta-analytics/.

Elitzur R. 2020. Data analytics effects in major league baseball. Omega. 90:102001. doi: 10.1016/j.omega.2018.11.010.

Epasinghege Dona N, Swartz TB. 2024. Causal analysis of tactics in soccer: the case of throw-ins. IMA J Manag Math. 35 (1):111–126. doi: 10.1093/imaman/dpad022.

Fernández J, Bornn L. 2018. Wide open spaces: a statistical technique for measuring space creation in professional soccer. *Proceedings of MIT Sloan Sports Analytics Conference.* Boston, MA, USA.

Fernández J, Bornn L. 2020. Soccermap: a deep learning architecture for visually-interpretable analysis in soccer. *Proceedings of the 2020 Joint European Conference on Machine Learning and Knowledge Discovery in Databases.* Ghent, Belgium, Springer), vol. 12461. p. 491–506.

Fernández J, Bornn LD, Cervone D. 2021. A framework for the fine-grained evaluation of the instantaneous expected value of soccer possessions. Mach Learn. 110(6):1389–1427. doi: 10.1007/s10994-021-05989-6.

Fernandez-Navarro J, Fradua L, Zubillaga A, Ford PR, McRobert AP. 2016. Attacking and defensive styles of play in soccer: analysis of Spanish and English elite teams. J Sports Sci. 34(24):2195–2204. doi: 10.1080/02640414.2016.1169309.

Fullagar HH, Mccall A, Impellizzeri FM, Favero T, Coutts AJ. 2019. The translation of sport science research to the field: a current opinion and overview on the perceptions of practitioners, researchers and coaches. Sports Med. 49 (12):1817–1824. doi: 10.1007/s40279-019-01139-0.

Gebru T, Morgenstern J, Vecchione B, Vaughan JW, Wallach H, , Iii HD, Crawford K. 2021. Datasheets for datasets. Commun ACM. 64(12):86–92. doi: 10.1145/3458723.

Goes FR, Kempe M, Meerhoff LA, Lemmink KA. 2019. Not every pass can be an assist: a data-driven model to measure pass effectiveness in professional soccer matches. Big Data. 7 (1):57–70. doi: 10.1089/big.2018.0067.

Goes FR, Meerhoff LA, Bueno MJ, Rodrigues DM, Moura FA, Brink MS, Elferink- Gemser MT, Knobbe AJ, Cunha SA, Torres RS, et al. 2021. Unlocking the potential of big data to support tactical performance analysis in professional soccer: a systematic review. Eur J Sport Sci. 21(4):481–496. doi: 10.1080/17461391.2020.1747552.

Graham I. 2024. How to win the Premier league: the inside story of football's data revolution. London, UK: Century.

Gregory S, Pleuler D, Daly-Grafstein D, Liu Y, Marchwica P. 2021. Pace and power: removing unconscious bias from soccer broadcasts. *Proceedings of New England Symposium on Statistics in Sports.* Virtual event.

Hecksteden A, Kempe M, Berger J. 2025. Perspectives on data analytics for gaining a competitive advantage in football: harnessing data for decision support. Sci Med Football. 1–9. doi: 10.1080/24733938.2025.2517056.

Hewitt A, Greenham G, Norton K. 2016. Game style in soccer: what is it and can we quantify it? Int J Perform Anal Sport. 16 (1):355–372. doi: 10.1080/24748668.2016.11868892.

Hirotsu N, Wright M. 2002. Using a Markov process model of an association football match to determine the optimal timing of substitution and tactical decisions. J Oper Res Soc. 53 (1):88–96. doi: 10.1057/palgrave/jors/2601254.

Hughes H, Horton M, Wei F, Stokl M, Gammulle H, Fookes C, Sridharan S, Pedagadi S, Lucey P. 2024. Approaching in-venue quality tracking from broadcast video using generative AI. *Proceeding of the MIT Sloan Sports Analytics Conference.* Boston, MA, USA.

Kharrat T, McHale IG, López Peña J. 2020. Plus–minus player ratings for soccer. J Eur J Oper Res. 283(2):726–736. doi: 10.1016/j.ejor.2019.11.026.

Kubatko J, Oliver D, Pelton K, Rosenbaum DT. 2007. A starting point for analyzing basketball statistics. J Quant Anal Sports. 3(3):1–24. doi: 10.2202/1559-0410.1070.

Le H, Carr P, Yue Y, Lucey P. 2017. Data-driven ghosting using deep imitation learning. *Proceedings of the MIT Sloan Sports Analytics Conference* Boston, MA, USA.

Le HM, Yue Y, Carr P, Lucey P. 2017. Coordinated multi-agent imitation learning. Proceedings of the 34th International Conference on Machine Learning. p. 1995–2003.

Lewis M. 2004. Moneyball: the art of winning an unfair game. New York, NY, USA: WW Norton & Company.

Liu G, Luo Y, Schulte O, Kharrat T. 2020. Deep soccer analytics: learning an action-value function for evaluating soccer players. Data Min Knowl Discov. 34(5):1531–1559. doi: 10.1007/s10618-020-00705-9.

Lolli L, Bauer P, Irving C, Bonanno D, Höner O, Gregson W, Di Salvo, V. 2024. Data analytics in the football industry: a survey investigating operational frameworks and practices in professional clubs and national federations from around the world. Sci Med Football. 1:1–10.

Lopez MJ. 2020. Bigger data, better questions, and a return to fourth down behavior: an introduction to a special issue on tracking data in the national football league. J Quant Anal Sports. 16(2):73–79. doi: 10.1515/jqas-2020-0057.

Lowe ZL. Lights, Cameras, Revolution. 2013. https://grantland.com/features/the-toronto-raptors-sportvu-cameras-nba-analytical-revolution/.

Lucey P, Bialkowski A, Mofort M, Carr P, Matthews I. 2015. Quality vs. quantity: improved shot prediction in soccer using strategic features from spatiotemporal data. *Proceedings of the MIT Sloan Sport Analytics Conference* Boston, MA, USA.

Lucey P, Bialkowski A, Monfort M, Carr P, Matthews I. 2015. Quality vs quantity: improved shot prediction in soccer using strategic features from spatiotemporal data. *MIT Sloan Sports Analytics Conference*.

Lundberg SM, Lee S-I. 2017. A unified approach to interpreting model predictions Proceedings of the 31st International Conference on Neural Information Processing Systems. Long Beach, CA, USA.

McRobert AP, Fernández-Navarro J, Seth, L. 2023. Technical and tactical match analysis. In: Williams AM, Drust B Ford P, editors. Science and soccer: developing elite performers. London, UK & New York, NY: Routledge.

Merckx S, Robberechts P, Euvrard Y, Davis J. 2021. Measuring the effectiveness of pressing in soccer. *Proceedings of the 8th Workshop on Machine Learning and Data Mining for Sports Analytics.* Virtual event.

Mitchell M, Wu S, Zaldivar A, Barnes P, Vasserman L, Hutchinson B, Spitzer E, Raji ID, Gebru T. 2019. Model cards for model reporting. *Proceedings of the conference on* *fairness, account- ability, and transparency*. Atlanta, GA, USA p. 220–229.

Narayanan S, Pifer ND. 2024. An xG of their own: using expected goals to explore the analytical shortcomings of misapplied gender schemas in football. J Sport Manage. 38 (2):92–109. doi: 10.1123/jsm.2023-0022.

Nori H, Jenkins S, Koch P, Caruana R. 2019. Interpretml: a unified framework for machine learning interpretability, ArXiv.

O'Donoghue P, Hughes M, 2019. Reliability issues in sports performance analysis. In: Hughes M, Franks I, Hughes M, Franks IM, Dancs H, editor. Essentials of performance analysis in sport. New York, NY, USA: Routledge.

O'Hanlon R. 2022. Net Gains: Inside the Beautiful Game's Analytics Revolution (New York, NY, USA: Abrams Press).

Omidshafiei S, Hennes D, Garnelo M, Wang Z, Recasens A, Tarassov E, Yang Y, Elie R, Connor JT, Muller P, et al. 2022. Multiagent off-screen behavior prediction in football. Sci Rep. 12(1):8638. doi: 10.1038/s41598-022-12547-0.

Pappalardo L, Cintia P, Ferragina P, Massucco E, Pedreschi D, Giannotti F. 2019. PlayeRank: data-driven performance evaluation and player ranking in soccer via a machine learning approach. ACM Trans Intell Syst Technol. 10(5):1–27. doi: 10.1145/3343172.

Pelechrinis K, Winston W. 2021. A skellam regression model for quantifying positional value in soccer. J Quant Anal Sports. 17(3):187–201. doi: 10.1515/jqas-2019-0122.

Peralta Alguacil F, Fernandez J, Arce P, Sumpter D. 2020. Seeing in to the future: using self-propelled particle models to aid player decision-making in soccer. *Proceedings of the MIT Sloan Sports Analytics Conference*. Boston, MA, USA p. 1–23.

Pleuler D 2014. On the topic of expected goals and the repeatability of finishing skill. http://www.optasportspro.com/about/optaproblog/posts/2014/on-the-topic-of-expected-goals-and-the-repeatability-of-finishing-skill.aspx .

Power P, Hobbs J, Ruiz H, Wei X, Lucy P. 2018. Mythbusting set-pieces in soccer. *Proceedings of MIT Sloan Sports Analytics Conference*. Boston, MA, USA.

Power P, Ruiz H, Wei X, Lucey P. 2017. Not all passes are created equal: objectively measuring the risk and reward of passes in soccer from tracking data. *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. Halifax, NS, Canada p. 1605–1613.

Raabe D, Biermann H, Bassek M, Wohlan M, Komitova R, Rein R, Groot TK, Memmert D. 2022. Floodlight - a high-level, data-driven sports analyticsframework. JOSS. 7(76):4588. doi: 10.21105/joss.04588.

Rahimian P, Toka L. 2022. Optical tracking in team sports: a survey on player and ball tracking methods in soccer and other team sports. J Quant Anal Sports. 18(1):35–57. doi: 10.1515/jqas-2020-0088.

Rahimian P, Van Haaren J, Abzhanova T, Toka L. 2022. Beyond action valuation: a deep reinforcement learning framework for optimizing player decisions in soccer. *Proceedings MIT Sloan Sports Analytics Conference*. Boston, MA, USA p. 25.

Rahimian P, Van Haaren J, Toka L. 2024. Towards maximizing expected possession outcome in soccer. Int J Sports Sci Coaching. 19(1):230–244. doi: 10.1177/17479541231154494.

Ribeiro MT, Singh S, Guestrin C. 2016. "Why should I trust you?": explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. San Francisco, CA, USA p. 1135–1144.

Robberechts P, Davis J. 2020. How data availability affects the ability to learn good xG models. *Proceedings of the 7th Workshop on Machine Learning and Data Mining for Sports Analytics*. Ghent, Belgium p. 17–27.

Robberechts P, Van Roy M, Davis J. 2023. Un-xpass: measuring soccer player's creativity. *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. Long Beach, CA, USA p. 4768–4777.

Rudd S. 2011. A framework for tactical analysis and individual offensive production assessment in soccer using Markov chains. *New England Symposium on Statistics in Sports*. Cambridge, MA, USA..

Rudolph Y, Brefeld U. 2022. Modeling conditional dependencies in multiagent trajectories. *Proceedings of the 25th International Conference on Artificial Intelligence and Statistics*. Virtual conference, p. 10518–10533.

Seebacher D, Polk T, Janetzko H, Keim DA, Schreck T, Stein M. 2023. Investigating the sketchplan: a novel way of identifying tactical behavior in massive soccer datasets. IEEE Trans Visual Comput Graphics. 29(4):1920–1936. doi: 10.1109/TVCG.2021.3134814.

Shaw L, Gopaladesikan S. 2021. Routine inspection: a playbook for corner kicks. *Proceedings of MIT Sloan Sports Analytics Conference*. Boston, MA, USA.

Shitrit HB, Berclaz J, Fleuret F, Fua P. 2011. Tracking multiple people under global appearance constraints. *Proceedings of 13th International Conference on Computer Vision*. Barcelona, Spain, IEEE. p. 137–144.

Shitrit HB, Berclaz J, Fleuret F, Fua P. 2013. Multi-commodity network flow for tracking multiple people. IEEE T Pattern Anal. 36(8):1614–1627. doi: 10.1109/TPAMI.2013.210.

Singh K. 2019. Introducing expected threat. https://karun.in/blog/expected-threat.html.

Spearman W. 2018. Beyond expected goals. *Proceedings of the MIT Sloan Sports Analytics Conference*. Boston, MA, USA.

Spearman W, Pop P, Basye A, Hotovy R, Dick G. 2017. Physics-based modeling of pass probabilities in soccer. *Proceedings of the MIT Sloan Sports Analytics Conference*. Boston, MA, USA.

Statsbomb H. 2021 Introducing on-ball value (obv). https://statsbomb.com/news/introducing-on-ball-value-obv/.

Statsperform. Introducing a possession value framework. https://www.statsperform.com/resource/introducing-a-possession-value-framework/.

Stein M, Seebacher D, Marcelino R, Schreck T, Grossniklaus M, Keim DA, Janetzko H. 2019. Where to go: computational and visual what-if analyses in soccer. J Sports Sci. 37 (24):2774–2782. doi: 10.1080/02640414.2019.1652541.

Straccia U, Pratesi F. 2022 eds. The TAILOR Handbook of Trustworthy AI (Online encyclopedia).

Sun X, Davis J, Schulte O, Liu G. 2020. Cracking the black box: distilling deep sports analytics. *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining*. Virtual event p. 3154–3162.

Szczepański L, McHale I, M I. 2016. Beyond completion rate: evaluating the passing ability of footballers. J Appl Psychol The Royal Statistical Society: Series A (statistics In Society). 179(2):513–533. doi: 10.1111/rssa.12115.

Taki T, Hasegawa J, Fukumura T. 1996. Development of motion analysis system for quantitative evaluation of teamwork in soccer games. *Proceedings of 3rd IEEE International Conference on Image Processing*. Lausanne, Switzerland), vol. 3. p. 815–818.

Van Haaren J. 2021. Why would I trust your numbers? on the explainability of expected values in soccer. *Proceedings of the AI for Sports Analytics (AISA) Workshop*. Virtual workshop.
Van Roy M, Robberechts P, Decroos T, Davis J. 2020. Valuing on-the-ball actions in soccer: a critical comparison of xT and VAEP. *Proceedings of the 2020 AAAI Workshop on AI in Team Sports*. New York, NY, USA.
Van Roy M, Robberechts P, Yang W-C, De Raedt L, Davis J. 2021. Leaving goals on the pitch: evaluating decision making in soccer. *Proceedings of the MIT Sloan Sports Analytics Conference*. Boston, MA, USA.
Van Roy M, Robberechts P, Yang W-C, De Raedt L, Davis J. 2023. A Markov framework for learning and reasoning about strategies in professional soccer. J Artif Intell Res. 77:517–562. doi: 10.1613/jair.1.13934.
Wang Z, Veličković P, Hennes D, Tomašev N, Prince N, Kaisers L, Bachrach M, Elie Y, Wenliang R, Piccinini LK, Tuyls K. 2024. TacticAI: an AI assistant for football tactics. Nat Commun. 15 (1). doi: 10.1038/s41467-024-45965-x.
West SW, Clubb J, Blake TA, Fern J, Bowles H, Dalen-Lorentsen T. 2024. Big data. Big potential. big problems? BMJ Open Sport Exerc Med. 10(2):e001994. doi: 10.1136/bmjsem-2024-001994.
Windt J, Taylor D, Little D, Sporer BC. 2021. Making everyone's job easier. how do data scientists fit as a critical member of integrated support teams? Br J Sports Med. 55(2):73–75. doi: 10.1136/bjsports-2020-102938.
Wu LY, Danielson A, Hu XJ, Swartz TB. 2021. A contextual analysis of crossing the ball in soccer. J Quant Anal Sports. 17(1):57–66. doi: 10.1515/jqas-2020-0060.
Yam D. 2019. A data driven goalkeeper evaluation framework. *Proceedings of the 13th MIT Sloan Sports Analytics Conference*. Boston, MA, USA p. 1–18.
Yeh R, Schwing A, Huang J, Murphy K. 2019. Diverse generation for multi-agent sports games. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. Long Beach, CA, USA p. 4610–4619.