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Original Article

Bridging the gap: Leveraging Power BI to connect data science and soccer coaches

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Abstract:
Background: The availability of statistical data in the field of football performance analysis is continuously expanding. Despite this abundance, the effective utilization of such data in practical scenarios encounters various challenges. **Purpose:** This study aimed to explore the potential of integrating visualizations through Power BI to the effectiveness of statistical analysis for soccer coaches. **Methodology:** We leveraged data from three Excel sheets derived from two surveys published in the "Journal of Physical Education and Sport". Employing Power BI, we created six distinct types of graphs. **Results:** The treemap depicts the distribution of corner kicks and resulting goals based on delivery type and zone. The area chart illustrates the team's season long form. The clustered column chart reveals goals, expected goals, and team efficiency. The radar chart depicts the team's behavior relative to the league's average across 19 tactical situations. The table heatmap presents the percentage of passes in each third of the pitch for the teams. The scatter bubble chart illustrates team performance across four distinct tactical situations during the attacking phase. **Conclusions:** The derived visualizations provided coaches with invaluable practical insights. Our findings underscore the significance of visualizing statistical data, thereby empowering coaches to analyze their team, assess opponents, and identify trends within their competitive landscape. Visualization proves to be an indispensable tool for making critical decisions and gaining a profound understanding of diverse performance aspects. By harnessing Power BI, coaches can adeptly interpret and capitalize on statistical information, resulting in refined analysis and more informed decision-making processes.
Keywords: football, visualization, performance analysis, statistical data, sports analytics

Introduction

Soccer, in comparison to other popular sports, is an inherently complex and chaotic game (Ferrarini, 2016) characterized by a high degree of freedom, which presents challenges for game analysis (Bley et al., 2022). As a result, performance analysis has become indispensable for football teams, with analysts now being an integral part of coaching staffs (Plakias, Moustakidis, Kokkotis, Tsatalas, et al., 2023; Wright et al., 2014). Analysis is conducted both qualitatively, using video, and quantitatively, employing statistical measures (Hughes, 2003; Rein & Memmert, 2016). However, qualitative analysis is subjective, necessitating an objective perspective offered by statistical data (Carling et al., 2007).

Recent technological advancements have led to the development of systems and devices capable of generating vast amounts of data (Memmert & Rein, 2018). Numerous companies, such as OPTA, Statsbomb, Instat, and Wyscout, provide teams with extensive statistical data (Rahimian & Toka, 2023; Tuyls et al., 2021). Plenty of statistical data for football matches are even provided by free websites on the internet, such as Fbref, Whoscored and others (Kapsalis et al., 2023; Plakias, Moustakidis, Kokkotis, Papalexi, et al., 2023). Consequently, the availability of statistical data in football has grown exponentially, posing a new challenge in terms of managing and effectively utilizing this data (Rein & Memmert, 2016).

The motivation behind this paper stems from two interviews featured in a book published with the conclusions of the 2nd Barça Sports Analytics Summit, organized by the Barça Innovation Hub (Ric & Peláez, 2020). Specifically, the former coach of the Spanish national team (Robert Moreno) stated that "The main limitation is that coaches and technical staff lack the training to make optimum use of the avalanche of data that we receive", while the Video Analyst of the German national team (Christopher Clemens) stated that "Data visualization is a key factor to translate abstract quantitative information into easy and intuitively understandable information for the coaches". Therefore, on one hand, a coach acknowledged that teams receive an overwhelming amount of data, which coaches are unable to fully leverage. On the other hand, an analyst emphasized the importance of data visualization as the optimal approach to ensure coaches can comprehend the information and effectively utilize it.

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Over a relatively brief period, there has been a significant expansion in both the scope and depth of academic research and practical implementation of performance analysis in the field (Plakias, Moustakidis, Mitrotasios, et al., 2023). There is substantial proof supporting the notion that performance analysis can offer impartial data, allowing for valuable insights and comprehension of technical and tactical performance indicators that are vital to football performance (Wright et al., 2014). However, traditional statistical analyses often present challenges for coaches to comprehend (Ali et al., 2016; Du & Yuan, 2021; Perin et al., 2018), highlighting the need for improved communication and understanding between data analysts, tactical analysts, and coaches (Rønningen, 2021).

Data visualization emerges as a solution to this issue (Soares Afonso, 2019). By representing data visually, clearly, and effectively, data visualization enables better communication between coaches and analysts, enhancing interpretability (Soares Afonso, 2019). In the book titled "Professional Practice in Sport Performance Analysis" the author Andrew Butterworth presents various types of graphical representations (Butterworth, 2023). In the critical review of the book, Plakias (2023) highlights the potential for additional graphical representations to be suggested. Visual representations can synthesize and communicate advanced findings in a practical manner that resonates with coaches (Pedersen, 2021). The visual representation of numbers facilitates pattern recognition and decision-making processes (Ali et al., 2016). Furthermore, visualization work provides a comprehensive reference for data analysis and supports decision-making (Du & Yuan, 2021). As a result, competitive sports data visualization and visual analysis have become prominent topics of research (Du & Yuan, 2021).

In recent years, researchers have proposed numerous valuable visualization methods and tools to aid analysts and coaches in identifying behavioral patterns and addressing specific challenges encountered during the analysis process (Du & Yuan, 2021). However, no study to date has suggested the utilization of Power BI as a decision-making tool for soccer coaches. Power BI, developed by Microsoft in 2015, is a business intelligence tool specifically designed for visualizing statistical data (Ferrari & Russo, 2017; Rajesh et al., 2020). It encompasses a suite of software services, applications, and plug-ins that collaboratively transform disparate data sources into cohesive, visual, and interactive displays. These data sources can include Excel spreadsheets or other formats (Doko & Miskovski, 2020). Power BI empowers users to load and select data fields for in-depth analysis, and provides a range of visualizations that best suit the data at hand (Becker & Gould, 2019; O'Toole, 2021). It is renowned for its user-friendly and efficient interface (Becker & Gould, 2019; Doko & Miskovski, 2020), generating impactful visualizations (Rajesh et al., 2020) that enhance users' understanding of the data, facilitate drawing conclusions, and support decision-making processes (Ali et al., 2016; Becker & Gould, 2019; Doko & Miskovski, 2020). Therefore, the objective of this research is to explore, through specific examples and utilizing real football match data, if the integration of Power BI can foster collaboration between analysts and coaches, enhance football coaches' comprehension of statistics, and ultimately improve the decision-making process in the coaching domain.

Material & methods

Three distinct Excel sheets from two previous surveys were imported into Microsoft Power BI Desktop for carrying out the present research. Specifically, we utilized the findings from the study conducted by Plakias, Kokkotis, Tsaopoulos, et al. (2023), focusing on corner efficiency in relation to the delivery type (HOW) and zone (WHERE), as illustrated in Figures 1 and 2. Additionally, the results of Factor Analysis from a study on playing style recognition (Plakias, Kokkotis, Moustakidis, et al., 2023) were incorporated. Table 1 presents both the latent variables, as named by the authors, and the corresponding styles associated with each latent variable, determined by the positive or negative sign of the factor scores in each observation. Furthermore, six variables from the original dataset (3rd Excel sheet) were selected from the same research, including Goals, xG (expected goals), INSTAT INDEX (a performance evaluation index developed by the company), and the passing percentages for each team in the three thirds of the field. Treemap, area chart, clustered column chart, radar chart, table heatmap, and scatter bubble chart were employed as examples to visualize the data.

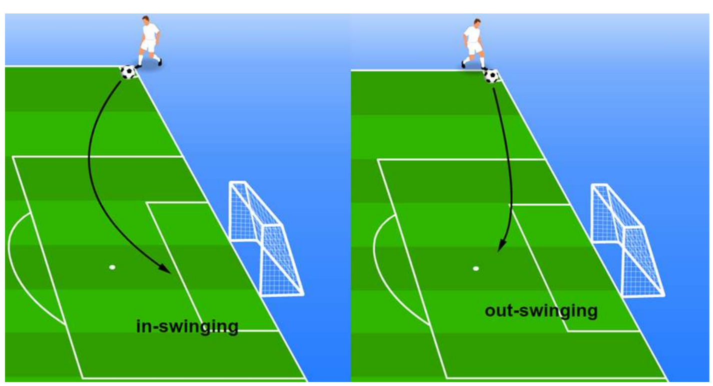

Figure 1. Delivery type

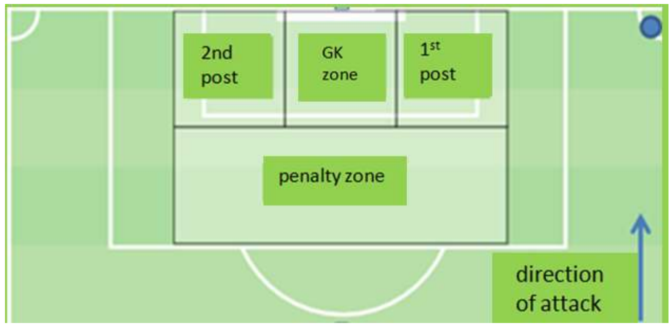

Figure 2. Delivery zones

Table 1. Latent variables and playing styles generated based on the sign (positive or negative) of factor scores in each observation.

FACTOR	LATENT VARIABLE	POSITIVE SCORES	NEGATIVE SCORES
F1	Elaboration of build up phase	Possession style	Direct style
F2	Transition game	Many transitions	Few transitions
F3	Attacking transition	Counterattack	Positional attack
F4	Defensive transition	Opponent's counterattack	Opponent's positional attack
F5	Aerial game	Game in the air	Game on the ground
F6	Type of attack	Set pieces attack	Open play attack
F7	Crossing	Many crosses	Few crosses
F8	Type of opponent's attack	Open play defense	Set pieces defense
F9	Defensive blocks	Mid block	Low block
F10	Press	High press	Deep press
F11	Individual defending actions	Many individual defending actions	Few individual defending actions
F12	Width of creative phase	Center attack	Wide attack
F13	Effective game	More interruptions and duels	More possession from one or the other team
F14	Individual attacking actions	Many individual attacking actions	Few individual attacking actions
F15	Tendency to create final attempts	Little possession required to generate final attempts (strong tendency)	High possession required to generate final attempts (low tedency)
F16	Passing tempo	Low passing tempo	High passing tempo
F17	Defending aggressively	Low defensive aggressiveness	High defensive aggressiveness
F18	Attacking aggressively	High attacking aggressiveness	Low attacking aggressiveness
F19	Offside trap	More frequent adoption of the offside trap	Less frequent adoption of the offside trap

Results

The treemap depicted in Figure 3 illustrates the distribution (in percentages) of corner kicks taken and the resulting goals based on delivery type and zone. By comparing diagrams 3a and 3b, it becomes evident that the blue color representing the 2nd post occupies a larger area in diagram 3b than in diagram 3a. This indicates that the percentage of goals scored from corners at the 2nd post is higher than the corresponding percentage for corner kicks executed in this zone. Additionally, for corner kicks taken at the 1st post (red color), it is noteworthy that although more corners were executed with an inswing type, a higher number of goals were scored with an outswing type. Lastly, in the penalty zone (grey color), it is noteworthy that no goals have been scored with the inswing type, despite a 5% occurrence of this type in that specific zone.

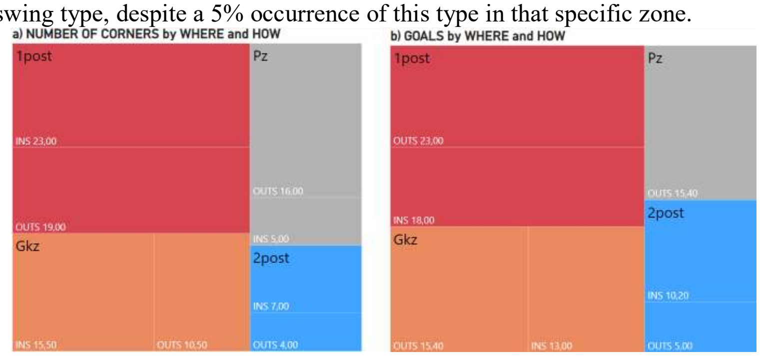

Figure 3. Number of corners (a) and Goals of corners (b)

The area chart in Figure 4 illustrates the INSTAT INDEX of the Wolves team throughout the season. From this chart, it can be observed that the team's performance was low (INSTAT INDEX < 235) during a three-game period (M12-M14), but then consistently high (INSTAT INDEX > 245) from game M15 until the M22 game.

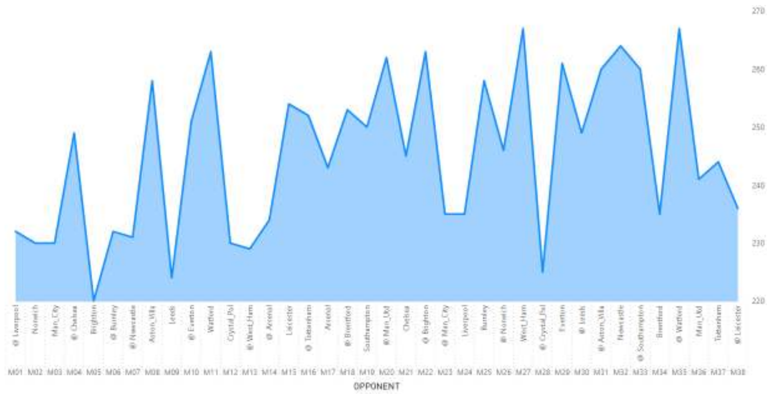

Figure 4. INSTAT INDEX for Wolves throughout the season.

The clustered column chart of Figure 5 shows the goals, the expected goals and the efficiency (obtained if the expected goals are subtracted from the goals) of all teams in the English Premier League. From this chart it can be seen that Leicester was the most efficient team, while Norwich was the least efficient. Likewise, the efficiency of all the teams can be observed.

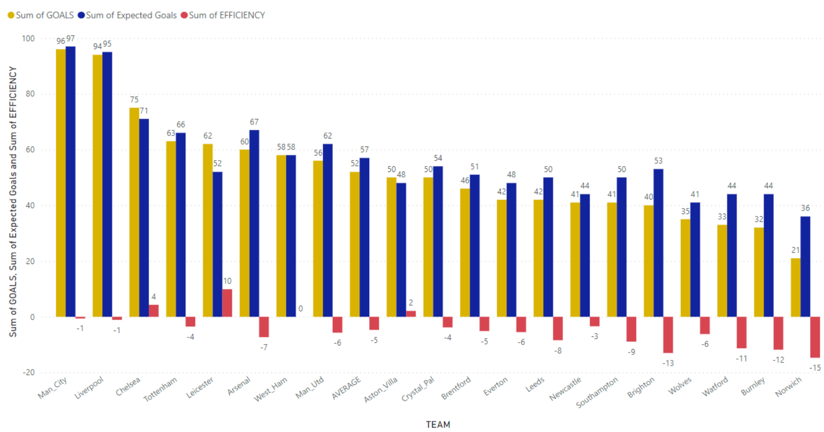

Figure 5. Goals, expected goals and efficiency for all teams in the English Premier League.

The radar chart in Figure 6 depicts the behavior of Wolves in comparison to the average of teams in the English Premier League across 19 tactical situations. It appears, for instance, that Wolves employ the high-press tactic (PRESS variable) less frequently than the average team in the English Premier League. Differences between Wolves and other teams can also be observed in the remaining 18 tactical situations.

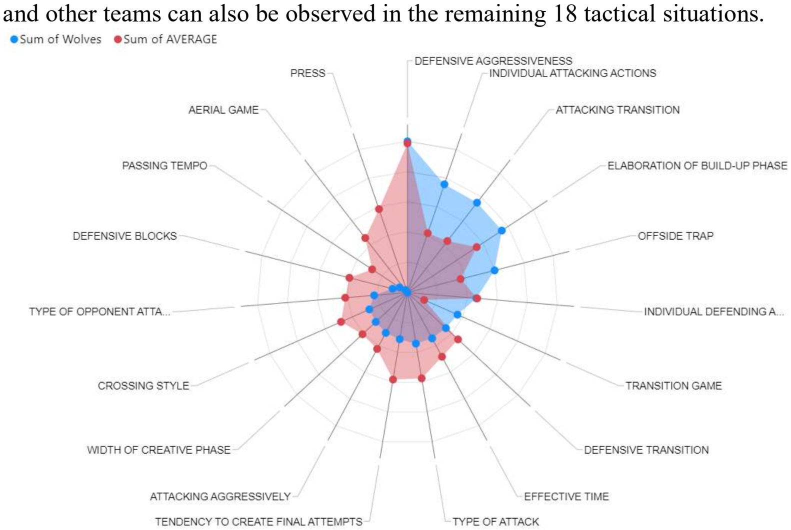

Figure 6. Mean Wolves factor scores relative to mean factor scores of English Premier League teams on the 19 latent variables.

The table heatmap in Figure 7 displays the percentage of passes in each third of the pitch for all teams in the English Premier League. This visualization reveals that higher-rated teams tend to make more passes in the middle and attacking third (indicated by darker colors towards the right of the table in these variables), whereas lower-rated teams tend to make more passes in the defensive third (indicated by darker colors in this variable).

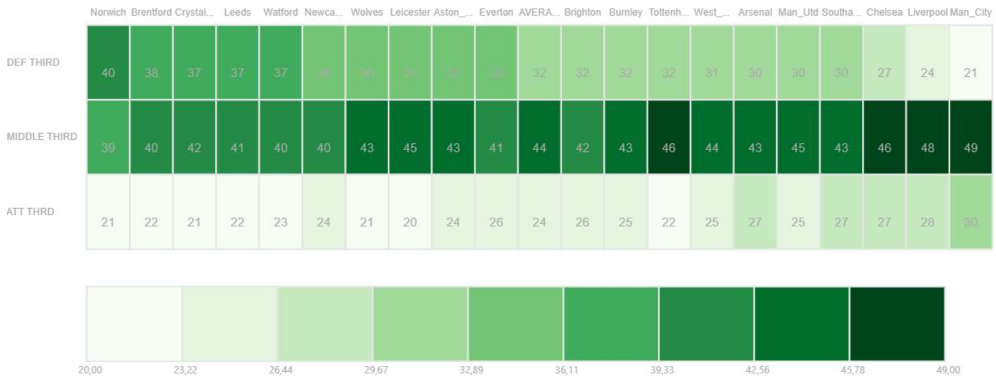

Figure 7. The percentage of passes in each third of the pitch for all teams in the English Premier League.

The scatter bubble chart in Figure 8 illustrates the performance of all teams in the English Premier League across four distinct tactical situations during the attacking phase. The x-axis represents the level of elaboration during the build-up sub-phase, while the y-axis represents the width during the creative sub-phase. The color of the bubbles indicates the passing tempo, while the size of the bubbles indicates the tendency to finish possessions with shots. From this chart, conclusions can be drawn regarding the attacking phase adopted by all teams in the English Premier League.

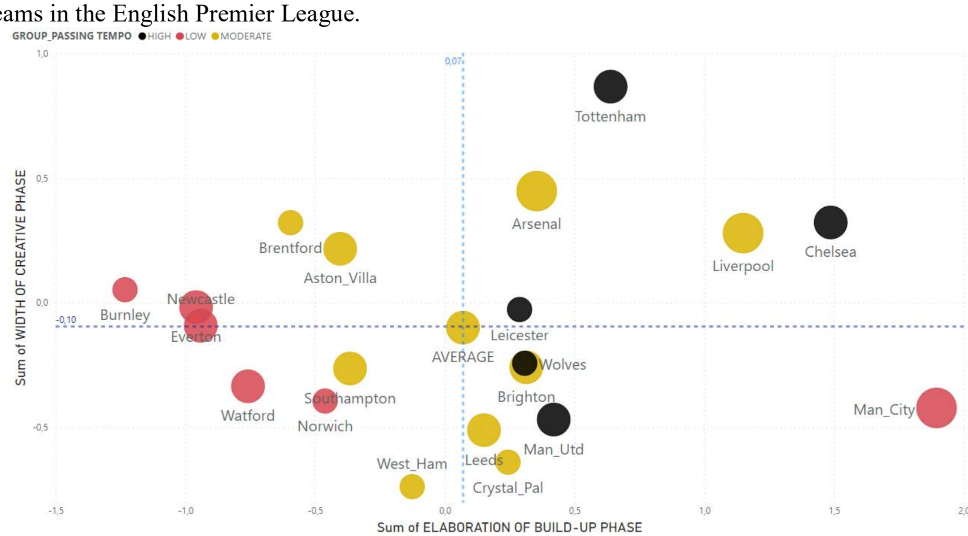

Figure 8. The performance of all teams in the English Premier League across four distinct tactical situations during the attacking phase.

Dicussion

In this study, we utilized data from previous research and employed the Power BI application to generate six distinct types of graphs. The outcomes demonstrated visually appealing representations of the data, which are easily comprehensible. Furthermore, these visualizations offer valuable insights into teams' tactics and can aid coaches in the decision-making process.

The treemap is a hierarchical visualization method (Schreck et al., 2006). It has been widely employed in various research studies, particularly in the business domain (Roberts et al., 2016; Vliegen et al., 2006; Ziegler et al., 2012), as well as in literature reviews (Almeida-Filho et al., 2021; Lv et al., 2014; Plakias, Moustakidis, Kokkotis, Tsatalas, et al., 2023). In this particular study, it is evident from images 3a and 3b that the treemap can provide coaches with valuable and straightforward insights regarding the selection of corner types and execution zones.

An area chart is essentially a variation of a line chart where the area between the x-axis and the line is filled with color or patterns (Oetting, 2019). It is particularly valuable for visualizing trends over a specific time period (Hardin et al., 2012). In the example presented in Figure 4, it illustrates the performance of a team throughout a competitive season. In soccer, area charts have also been utilized to depict variations in training load (Scott et al., 2013) during a series of training sessions, as well as changes in variables (e.g., speed) during a match (Benito Santos et al., 2018).

A clustered column chart is a vertical bar chart that displays separate bars for each category (Aspin, 2021). This chart type is particularly useful for highlighting significant differences, as demonstrated in the example shown in Figure 5. Conclusions can be drawn regarding the effectiveness of each team in converting possessions into goals, considering both the actual goals achieved and the expected goals based on the final attempts. This chart is commonly employed in research to depict differences pre and post the implementation of a protocol (Dainese et al., 2023; Olmedilla et al., 2019; Silvestre et al., 2006).

The radar chart is a graphical representation of multivariate data displayed on a two-dimensional plot with multiple variables originating from the same point (Möller, 2023). In the context of this research, it was employed to showcase a team's performance across 19 distinct tactical situations Figure 6). Its significance in assessing performance and estimation has been acknowledged in the international literature (Peng et al., 2019; Porter & Niksiar, 2018).

A table heatmap presents rating information ranging from high to low or poor to excellent. This rating information is conveyed through the use of distinct colors or varying saturation (Oetting, 2019). In the context of this research, the heatmap was employed to showcase variances among teams in terms of passing within each third of the pitch (Figure 7). Its significance in Sports Data Visualization has been emphasized by Perin et al. (2018), who highlight its applicability in illustrating disparities between events occurring in different zones of the field.

Lastly, a bubble chart is a variant of the scatter chart that incorporates additional data series by modifying the size and diameter of the bubbles (Su, 2008). In this study, it was utilized to illustrate the behavior of teams across four distinct tactical situations related to the attacking phase (Figure 8). By employing this visualization technique, coaches can obtain a more comprehensive understanding and draw informed conclusions. Previous researchers, such as Pollard et al. (1988), Fernandez-Navarro et al. (2016), Lago-Peñas et al. (2017), Castellano and Pic (2019), and Ruan et al. (2022) had employed a similar approach, albeit limited to two tactical situations, utilizing dots instead of bubbles.

With regard to the limitations of the present study, there are some aspects that should be highlighted. Firstly, this research exclusively utilized Power BI for data visualization and did not explore other applications such as Tableau (Hoelscher & Mortimer, 2018) or programming languages like R and Python (Lebanon et al., 2018). However, it is important to note that Power BI offers interactive and intuitive visualizations, enabling users to explore data and derive valuable insights. Moreover, it provides a user-friendly interface, simplifying the process of creating visualizations even for non-technical users. This aspect is particularly significant as some teams may lack specialized data scientists, and the responsibility of data analysis falls upon performance analysts. Additionally, the study only employed 6 different chart types out of the wide array of charts offered by Power BI. Future researchers can explore other chart examples capable of providing valuable information in the field of performance analysis, as well as consider the adoption of alternative tools.

Conclusions

Despite any limitations, this research has successfully demonstrated the potential of integrating Power BI as a tool to facilitate collaboration between analysts and coaches, enhance coaches' understanding of statistics, and ultimately improve the decision-making process in the coaching domain. Different chart types such as treemaps, area charts, clustered column charts, radar charts, table heatmaps, and bubble charts are used to visualize various aspects of team performance and tactical situations. Overall, by utilizing real football match data and providing specific examples, the study showcased how Power BI can effectively visualize complex statistical information, making it accessible and comprehensible to coaches, and giving them useful information both about their team and their opponents. Consequently, the integration of Power BI holds the potential to positively impact the field of football coaching by harnessing the power of data and statistics to drive success on the field. Therefore, our paper, in addition to its contribution to international literature by addressing a critical gap, holds substantial practical significance for coaches and their collaboration with performance analysts.

Conflicts of interest: We have no conflicts of interest to disclose.
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