Assessing and Visualizing Principles of Play in Soccer

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Abstract: Recent advances in soccer analytics have significantly expanded the use of spatial and temporal data to understand tactical behaviour. However, many visualisation tools remain limited in their ability to contextualize these behaviours according to established principles of play. This paper presents a context-aware visualisation framework that leverages StatsBomb Open Data to identify, illustrate, and interpret tactical patterns in professional soccer. The tool enables analysts to explore match phases through key tactical dimensions such as compactness, pressing, width, support, and penetration, using event-level data enriched with positional data (360 freeze frames). Unlike generic dashboards or statistical summaries, the proposed system integrates spatial relationships and collective movements, offering a more accurate representation of team behaviour across different match contexts. By combining visual methods with tactical theory, the tool supports coaches and analysts in identifying the match principles of play, thereby facilitating a deeper understanding of performance dynamics.

1 INTRODUCTION

In today's soccer, vast amounts of data are collected during matches, including player tracking data and event records, like passes, dribbles and shots. However, raw data must be transformed into actionable insights that accurately reflect the match context and can be interpreted by the coaching staff to inform their tactical decisions (Liu, 2022).

Data visualisation techniques convert complex numerical and spatial data into visual representations that highlight features or patterns relevant to tactical analysis. These methods assist analysts and coaches in identifying recurring behaviours, comparing player performance in specific contexts, and improving communication within the technical team (Perin et al., 2018; Liu, 2022). For example, visual tools can illustrate how a team constructs attacking sequences, the zones where players exert spatial dominance, or the structural variations in formation across different match phases (Krishnamurthy and Nanda, 2021; Bauer et al., 2023).

Over time, visualisation approaches have progressed from static or aggregated outputs like heatmaps and radar charts to more advanced, interactive systems. These include animated movement trajectories, dynamic passing networks, and formation models that evolve throughout the match (Sacha et al., 2017; Krishnamurthy and Nanda, 2021; Janetzko et al., 2014).

The core function of these tools is to extract and interpret features and tactical structures from the flow of the match. This includes recognizing repeated movement patterns, coordinated passing sequences, and adaptive behaviours (for example, responses to changes in possession status). Some systems can even detect which structural breakdowns contributed to match outcomes by contrasting successful and unsuccessful performance profiles (Krishnamurthy and Nanda, 2021).

Nonetheless, several challenges remain. Notably, there is no standardization in how visualisations represent time and space, which are fundamental to understanding the dynamics of soccer (Sotudeh, 2025; Bauer et al., 2023). Consequently, many tools fail to incorporate core tactical concepts such as the principles of play, offering visual summaries that lack the contextual depth required for high-level analysis.

In this context, this paper examines existing visualisation systems and evaluates how effectively they support the identification and interpretation of tactical patterns within professional soccer matches. Fur-

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thermore, this paper presents a solution to detect tactical principles of play in soccer through the combination of event-level data and 360 freeze frames from the StatsBomb Open Data model. The term ”principles of play” refers to a set of fundamental tactical guidelines that govern how teams organize and behave collectively during a soccer match such as pressing, compactness, width, support, and penetration, which emerge throughout different phases of play.

2 RELATED WORK

Over the past decade, several researchers have proposed advanced methods to enhance tactical insights. Among them are approaches relying on static or aggregated representations such as heatmaps, radar charts, and passing network diagrams. While effective for summarizing performance data, these visualisations fall short in capturing the full tactical complexity of the match, particularly the spatial and temporal dynamics that underpin team behaviour (Janetzko et al., 2014; Krishnamurthy and Nanda, 2021).

Perin et al. (2018) presented a comprehensive review of sports data visualisation, classifying existing work by its goals, target users, and data complexity. They also emphasize that working closely with coaches and analysts during the design process is essential to create tools that are not only functional, but also practical and relevant in real-world settings. In terms of goals, the authors give examples such as design studies with sports commentators, user need analysis, algorithm and model development, integration into real-world environments, and new visual or interaction techniques recommendations. With regards to target users, the work distinguishes between analysts and coaches and athletes (in practical evaluation tasks, usually), fans and the general public (in turn accessed via infographics), and journalists or data specialists. Finally, the authors define three categories of sports data: box score data (event data per individual match), tracking data (spatio-temporal movement data), and meta-data (contextual data like player profiles or stadium features).

The later classification criteria taps into the core of our proposal, namely in the fact that the vast majority of visualization tools fall into only one of these categories, hindering their capability to unveil features or patterns actionable into principles of play related tasks.

In addition to this classification, Table 1 groups seminal studies on soccer analytics research based on the following criteria: visualisation type and tactical analysis level. This overview enables us to distinguish between static and dynamic approaches, the level of user engagement, and the tactically investigated granularity each approach focuses on (individual or team level).

Most visualization tools use positional data. Liu (2022) explored geo-visualisation techniques for the analysis of player positioning data. This study uses tools such as Python, R, and GIS platforms to visualize spatial and spatio-temporal patterns, with emphasis on position-level tactical dynamics. Liu (2022) investigated how player tracking data can be animated and visualised using GIS tools and web technologies such as Python, HTML5, and Tableau. These tools add spatial and spatio-temporal context to soccer analytics, which is essential for understanding tactical positioning. As illustrated in Figure 1, simple player positional data can be combined with other more complex positional features such as convex hulls and Voronoi diagrams.

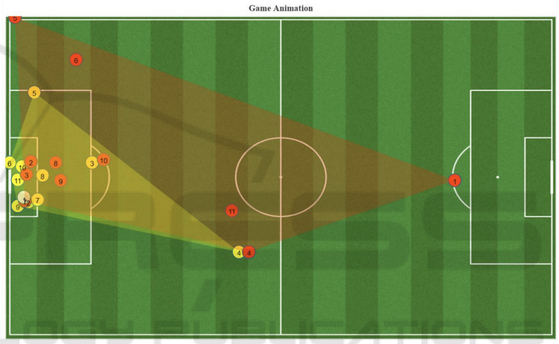

Figure 1: Interactive visualisation of player positions and convex hull selection interface. Adapted from Liu (2022).

In other research, Sacha et al. (2017) introduced a dynamic visual abstraction method that enables the analysis of collective player movement patterns. Their approach emphasizes the importance of movement over time, capturing dynamic tactical structures such as defensive lines and team pressing. Sacha et al. (2017) also propose visual abstraction techniques that simplify player movement patterns (see Figure 2), making it easier for analysts to observe and interpret tactical behaviour over time. In this application, instead of a single snapshot of the positional status of the match, the aggregated positions along a certain time interval are presented.

Other tools present values associated usually with player or team performance. These values can be superimposed or embedded in pitch diagrams (notable examples are pass networks and positional heat maps) or use other visual references (notable examples are radar charts). One example of the later is illustrated in Figure 3 from Liu (2022) where these charts are

Table 1: Comparison of visualisation approaches in soccer analytics literature.

Author (Year)	Visualisation Type	Level of Tactical Analysis
Liu (2022)	Geo-visualisation	Position Level
Sacha et al. (2017)	Dynamic	Team Level
Janetzko et al. (2014)	Static + Exploratory	Team Level
Krishnamurthy and Nanda (2021)	Interactive Dashboard	Team Level
Bauer et al. (2023)	Static Analysis	Team Level
Delibas et al. (2019)	Visual Analytics Tool	Team Level
Sotudeh (2025)	Conceptual/Survey	Both

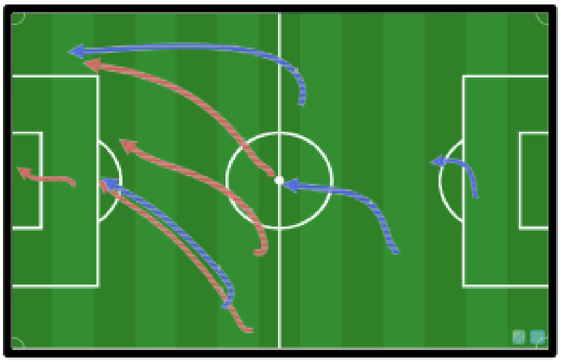

Figure 2: Visual representation of player movements through dynamic abstraction techniques. Adapted from Sacha et al. (2017).

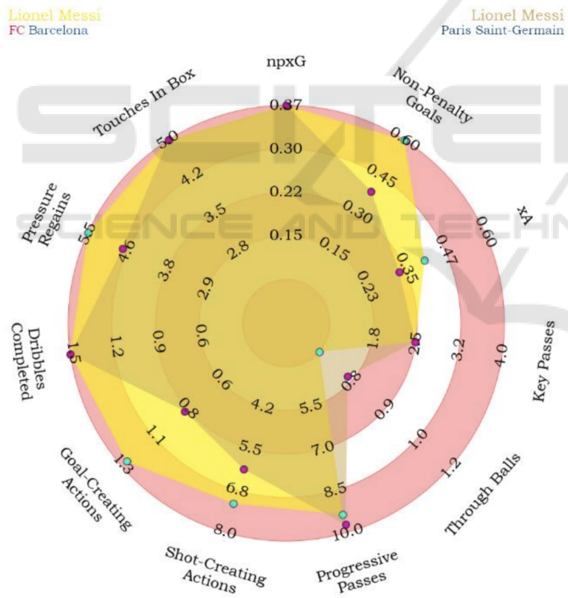

Figure 3: Radar chart illustrating statistical metrics for player performance. Adapted from Liu (2022).

used to represent different performance metrics of a specific player.

Several other studies have adopted varied visualization approaches, such as an interactive dashboards developed to visualize performance metrics at both player and team levels, using radar charts, heatmaps, and passing networks to analyse individual contribution and collective strategy (Krishnamurthy and Nanda, 2021). In addition, Janetzko et al. (2014) proposed a feature-oriented visual analytics framework bringing together static and exploratory visualisations, combining team measures enabling the discovery of patterns by using interactive filtering and brushing capabilities. Furthermore, an interactive exploratory analysis tool was introduced by Delibas et al. (2019) to investigate soccer event data through customizable parameters, supporting team-level tactical assessments by linking event-based data with visual analytics features. Taken together, these contributions demonstrate that different forms of visualisation, from dashboards to exploratory analysis frameworks, play an important role in helping analysts identify relevant patterns, understanding collective behaviour, and supporting decision-making processes in football analytics.

In recent years, more dynamic and interactive visualisation systems have emerged. One notable example is SoccerMetrics, an open-source framework that identifies key players, analyses strategies against different opponents, and highlights tactical changes associated with unsuccessful match outcomes (Krishnamurthy and Nanda, 2021).

One important area in development is recognising how formations evolve across different phases of the match. Sotudeh (2025) presented a comprehensive review on tactical formation identification. Their analysis goes from position-level and team-level perspectives, discussing data preprocessing, clustering, and template-based methods, while also highlighting methodological limitations and future directions.

Studies focused on tactical formations have also gained attention in recent years. Bauer et al. (2023) utilized static visual analysis to contextualize team formations, providing a conceptual framework to understand the variability of tactical structures under different match conditions. In addition, they employed a combination of convolutional neural networks and tracking data to segment matches into phases and detect formation changes beyond static labels like “4-4-2”. Similarly, Sotudeh (2025) reviewed principles for identifying formations and argued that many current methods oversimplify them by relying on spatial averages and clustering, often ignoring the temporal context of the match and the emergence of dynamic behaviours. Together, these studies emphasise the importance of moving beyond static representations to approaches that capture the fluid and dynamic nature of formations throughout a match.

Even with recent progress, many tools still rely heavily on aggregated data or static views, falling short in representing the fluid and complex dynamics of team play (Sotudeh, 2025; Bauer et al., 2023). Traditional heatmaps and static pass maps are often insufficient to represent interaction between players or the effect of context like match state or opponent strategy (Janetzko et al., 2014). Moreover, several tools rely heavily on event data, which lacks full spatial context, and under-use the rich potential of tracking data when not combined with tactical insights (Perin et al., 2018).

Other options are commercial platforms, such as Stats Edge Analysis, that provide analysts with the capability to examine tactical behaviour through interactive visual interfaces. These systems also provide synchronized positional and event information access, allowing one to filter periods of play (e.g., attack, defence, transition), select specific match situations, and project team arrangements onto a tactical board. One key component of this technology is the ability to automatically measure spatial statistics—such as team length, width, and compactness—that are directly applied to pitch maps for simpler interpretation.

In Stats Edge Analysis, for instance, people can distinguish average positioning of a player across selected sequences of matches and assess coordinated collective behaviours like coordination of pressing, line compactness, and block height. The system also supports custom queries by ball position and player role and offers dynamic frame-by-frame playback to put tactical trends in context. This spatial-temporal data-driven technology enables pre-match and post-match analysis, opponent team scouting, and detection of structural weaknesses or strengths.

Although existing visualisation tools offer useful summaries of performance data, they often fail to capture the underlying tactical complexity of soccer. Tactical principles are defined as spatial and temporal patterns that recur across matches. They help determine how teams act throughout different phases of the match. However, current tools rarely account for these principles, limiting their ability to support training design, match analysis, and tactical decision-making (Table 2). Consequently, there is a need for visualisation systems explicitly guided by principles of play, which can more effectively inform coaches and analysts.

3 StatsBomb DATA

StatsBomb Open Data is one of the most widely used open datasets in soccer analytics research. It provides detailed match-level data in JSON format, freely accessible for academic and non-commercial use. The data covers various professional competitions and includes structured information about competitions, matches, player line-ups, match events, and spatial context via 360 freeze frames. Each data type is organized in separate files, allowing modular and layered analysis of soccer performance.

3.1 Competitions and Matches

The `competitions.json` file lists all available competitions and seasons, including metadata such as country, sex, and competition IDs (StatsBomb, 2019a). Each competition is associated with one or more seasons, and matches are grouped under these seasons using the `matches.json` files (StatsBomb, 2019d). Each match entry contains information such as team names, match date, score, stadium, referee, and a unique `match_id` used to access further data files.

3.2 Line-Ups

The `lineups.json` files describe the starting eleven and substitutes for each team in a given match. For each player, the dataset includes their ID, full name, nickname, jersey number, and nationality (StatsBomb, 2019c). This data is crucial for linking actions and roles to specific individuals during the analysis.

3.3 Events

The event data is the analytical core of the dataset. Stored in `events.json` files, it includes all the on-the-ball actions performed during a match. Each event is timestamped and linked to a player, team, and spatial location on the pitch (StatsBomb, 2019b). The event types cover actions such as passes, dribbles, shots, fouls, interceptions, pressures, and more. Additional context is provided through tags like `under_pressure`, `carry`, `counterpress`, and `play_pattern`, which support more detailed tactical analysis.

StatsBomb describe in their open-data documentation that every on-the-ball event is tagged manually by analysts watching match videos. They follow a protocol that defines the type of event, who was involved and its time and pitch location.

Table 2: Core tactical principles, their definitions and application context.

Type	Principle	Description
Team Without Ball	Pressing	Immediate pressure on the ball carrier to force a mistake or regain possession.
	Compactness	Players stay close together, reducing space and blocking passing options.
	Coverage and Balance	Maintain defensive structure by covering space left by the pressing player.
	Containment	Delay the opponent's advance without trying to win the ball immediately.
	Control	Control tempo and dangerous zones with structured positioning.
Team With Ball	Penetration	Break defensive lines using passes, dribbles, or forward runs.
	Space Creation	Stretch the opponent's defence through width, movement, or decoys.
	Player Movement	Off-ball actions that unbalance opponents and open new options.
	Support	Stay close to the ball carrier to provide safe passing options.
	Creativity	Unpredictable actions like dribbles or disguised passes to destabilise defences.

3.4 Positional Data: 360 Freeze Frames

Positional data is provided with more detail, i.e., involving more players, in the 360 freeze frame data layer of the dataset (StatsBomb, 2021). Each freeze frame captures a snapshot of the pitch at the moment of a key event (e.g., a pass or shot). It includes the locations of nearby players in the visible area of the pitch based on a broadcast camera. Each player in the frame is tagged with their position on the field and whether they are a teammate or opponent.

3.5 Limitations

Although StatsBomb Open Data is highly detailed it presents some limitations. Notably, the 360 freeze frame positional data is not available for all competitions and, when available, it does not provide continuous tracking data for all 22 players, but rather static snapshots around events (i.e., there is no data between events) and event focus players.

Due to the limited capture scope of the broadcast cameras, positional data is not provided for all players in the pitch but only for those in the visible are of the camera (as illustrated in Figures 4 to 8). When players are out of the broadcast camera scope, they are temporarily not included in the freeze frame data until they reappear in subsequent frames. Moreover, each 360 freeze frame data only identifies the player performing the event (i.e., the actor) other players are tagged simply as from the same or opposing team to the actor, therefore limiting player-specific tracking analysis.

However, the data always captures the ball, the ball carrier, and the surrounding context of the action, which ensures that event-based metrics such as passes, shots, dribbles, pressures and duels are not affected. Although hampering metrics that depend on the full pitch coverage and identification of all players (e.g., team width, compactness, and spatial control), Statsbomb positional data still allows for the study of general spatial behaviour and team structure.

4 VISUALISATION TOOL

The developed visualisation tool is supported by neural networks and enables the exploration of tactical patterns in soccer with a focus on supporting coaches and analysts in understanding key principles of play. Built on top of StatsBomb Open Data, the tool allows the user to filter, extract, and visualise sequences of play where tactical behaviours emerge—such as compactness, width, support, and pressing.

As discussed earlier, tactical principles (see Table 2) are recurring patterns of collective behaviour that guide how teams act during different phases of the match. They help structure training, inform match analysis, and support decision-making by coaches and analysts. Tactical principles are typically divided into two categories: with-ball principles, which govern attacking behaviour, and without-ball principles, which relate to defensive organisation.

4.1 Tactical Principles Without Ball

Pressing

Pressing involves applying immediate pressure on the opponent with the ball, especially during transitions, to force mistakes or rushed decisions. It aims to disrupt the opponent's rhythm and recover possession quickly, preferably near the goal (Rein and Memmert, 2016; Forcher et al., 2024).

Pressure effectiveness can be measured by the opponent's response time:

$$t_r = t_{\text{pressure}} - t_{\text{decision}} \tag{1}$$

Where t_{pressure} and t_{decision} correspond to the time when pressure is applied and the time the opponent reacts. These two timestamps are relevant not only for computing the interval, t_r, but also as time boundaries for visualization representation of this principle.

Additionally, the number of passes forced or intercepted under pressure can be evaluated as:

$$P_f = \sum_{i=1}^{n} P_i, \quad P_i = \begin{cases} 1 & \text{if forced or intercepted} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Here, P_f and P_i correspond to the total pressured passes and the number of individual pass outcome.

Figure 4 from the developed visualization tool, illustrates pressure on a pass action.

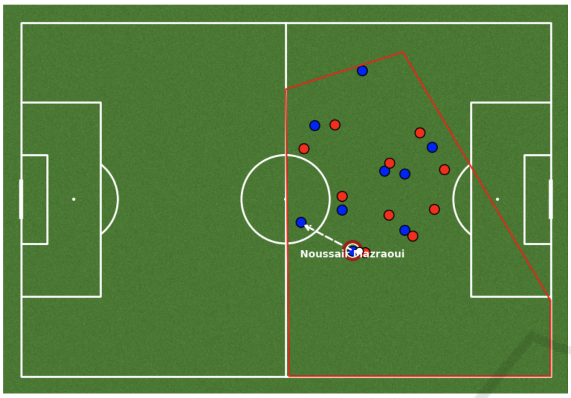

Figure 4: Pressure: Player under pressure, highlighted with a red circle. The white line indicates the destination of the next pass. The red polygon represents the visible area of the broadcast camera.

Compactness

Compactness refers to the team's ability to remain close together, minimising spaces between players and lines. This limits the opponent's passing options and enhances the collective defensive response (Plakias et al., 2024; Meerhoff et al., 2019).

A useful metric is the average distance between teammates:

$$\bar{d} = \frac{1}{n} \sum_{i,j=1, i \neq j}^{n} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{3}$$

where x_i, y_i and x_j, y_j are player i and j spatial coordinates; and $\bar{d}$ is the average pairwise distance.

We can also calculate how much space the team occupies on the field:

$$C_i = \frac{A_{\text{field}}}{A_{\text{team}}} \tag{4}$$

where A_{field} corresponds to the total field area and A_{team} the area covered by a particular team.

And assess their compactness via the Stretch Index:

$$S_i = \frac{\max_{i,j}(d_{i,j})}{\bar{d}(i,j)} \tag{5}$$

here $\max(d_{i,j})$ is the maximum distance between player pairs and $\bar{d}(i,j)$ its mean value.

This principle of play is illustrated in Figure 5 from the visualization tool. Here the possible pairs from each team are represented using the Delaunay triangulation.

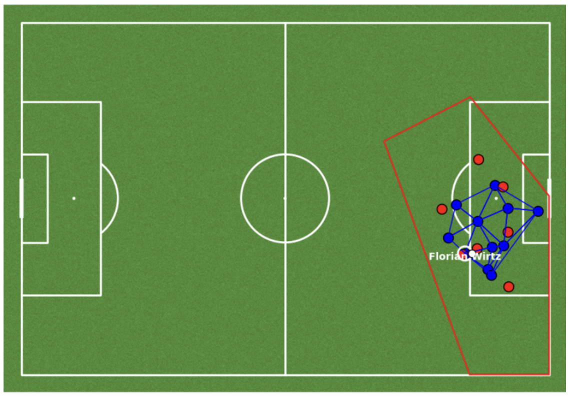

Figure 5: Compactness: Visual representation of team compactness using Delaunay triangulation.

Coverage and Balance

This principle ensures that the team maintains structure when pressing by repositioning nearby players to cover the space left by the presser. It provides defensive balance and avoids opening exploitable gaps (Plakias et al., 2024; Herold et al., 2019).

The proximity between pressing and covering players is essential and given by the Euclidean distance between pressing and covering players:

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{6}$$

where x_1, y_1 and x_2, y_2 are the coordinates of pressing and covering players.

We can quantify the fraction, B of players maintaining their defensive roles:

$$B = \frac{N_{\text{def}}}{N_{\text{total}}} \tag{7}$$

where N_{def} is the number of players in defensive roles and N_{total} the total number of players.

And evaluate team balance using its centroid:

$$C_x = \frac{1}{n} \sum_{i=1}^{n} x_i, \quad C_y = \frac{1}{n} \sum_{i=1}^{n} y_i \tag{8}$$

where C_x, C_y is the team centroid coordinates; and x_i, y_i the coordinates of each player of the focus team.

Containment

Containment slows down the opponent's offensive momentum without direct ball recovery attempts. It forces lateral or backward play and provides time for team reorganization (Rein and Memmert, 2016; Forcher et al., 2024).

The defender's reaction time, t_r is given by:

$$t_r = t_{\text{decision}} - t_{\text{pressure}} \tag{9}$$

where t_{decision} and t_{pressure} correspond to the opponent's action defender's approach timestamps.

Passes blocked or intercepted during containment are measured as:

$$I = \sum_{i=1}^{n} I_i, \quad I_i = \begin{cases} 1 & \text{if pass } i \text{ is intercepted} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where I is the total interceptions and I_i = binary indicator of interception (or not) for pass i.

Control

Control reflects the ability to dictate space and rhythm defensively, usually by positioning to block dangerous zones and slow the match's tempo Nouraie et al. (2023).

The controlled area, A_c, can be estimated by:

$$A_c = d \times P_b \tag{11}$$

here d stands for the defender's proximity and P_b the number of blocked passes.

Possession time while maintaining defensive control, t_c is:

$$T_c = t_{\text{possession}} - t_{\text{interception}} \tag{12}$$

where $t_{\text{possession}}$ and $t_{\text{interception}}$ correspond to the start of controlled possession and interception timestamps.

4.2 Tactical Principles with Ball

Penetration

Penetration is the ability to move the ball past defensive lines using passes, dribbles, or forward runs and is key to disrupting defensive structures and creating chances (Bauer and Anzer, 2021; Rein and Memmert, 2016).

The forward progress achieved, d, via pass or ball carry, is given by:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{13}$$

where x_1, y_1 and x_2, y_2 are the initial and final positions.

In addition to the pitch progress we can also count the number of successful penetrative passes, P_s as:

$$P_s = \textstyle\sum_{i=1}^{n} P_i, \quad P_i = \begin{cases} 1 & \text{if line-breaking pass is completed} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

where P_i is an indicative binary function associated to progressive pass completion. Figure 6 illustrates the representation of a progressive pass situation.

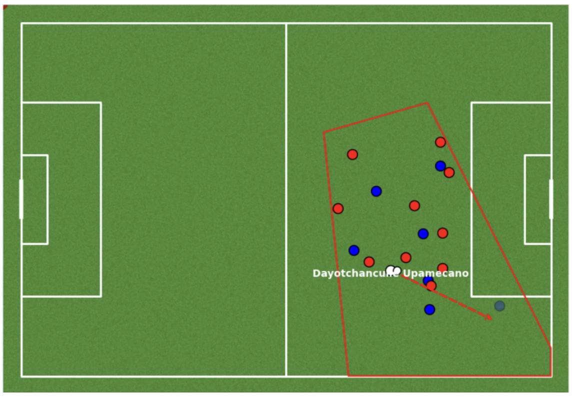

Figure 6: Example of a penetrative pass breaking the defensive line.A red dashed line with an arrow represents the penetrating pass.The faded point indicates the player who will receive the ball in the next frame.

Space Creation

Space creation stretches the opposing defence using width, movement, and decoy runs. It helps open passing lanes and create favourable match-ups (Stival et al., 2023; Caldeira, 2023; Meerhoff et al., 2019).

The available space generated, A_s is:

$$A_s = A_{\text{total}} - A_{\text{occupied}} \tag{15}$$

where A_{total} is full field area and A_{occupied} the used area.

The Stretch Index, S_i also applies here:

$$S_i = \frac{\max_{i,j}(d_{i,j})}{d(\bar{i}, j)} \tag{16}$$

where $\max(d_{i,j})$ is the maximum inter-player distance and $d(\bar{i}, j)$ is the average inter-player distance.

Player Movement

This principle involves intelligent off-ball movement to unbalance defences, either by dragging defenders away or creating new passing lanes (Bauer and Anzer, 2021; Rein and Memmert, 2016; Plakias et al., 2024).

We can measure the frequency of such movements, M_s as:

$$M_s = \textstyle\sum_{i=1}^{n} M_i \quad M_i = \begin{cases} 1 & \text{movement creates passing option} \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

here M_i is a binary indicator function for meaningfulness of movement i.

Support

Support ensures that the ball carrier has immediate and safe passing options nearby, enabling fluid and continuous attack (Muacho et al., 2022; Bauer and Anzer, 2021; Rein and Memmert, 2016).

The total number of supported passes, P_r is:

$$P_r = \sum_{i=1}^{n} P_i, \quad P_i = \begin{cases} 1 & \text{if pass is received} \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

here P_i is a binary indicator function if pass i had support (or not).

In addition to the number of supported passes, the distance, d_s between the ball carrier and a support player can also be computed as:

$$d_s = \sqrt{(x_{\text{player}} - x_{\text{pass}})^2 + (y_{\text{player}} - y_{\text{pass}})^2} \tag{19}$$

where $x_{\text{player}}, y_{\text{player}}$ and $x_{\text{pass}}, y_{\text{pass}}$ are the positional coordinates for the player with ball and its support player. Figure 7 illustrates this concept.

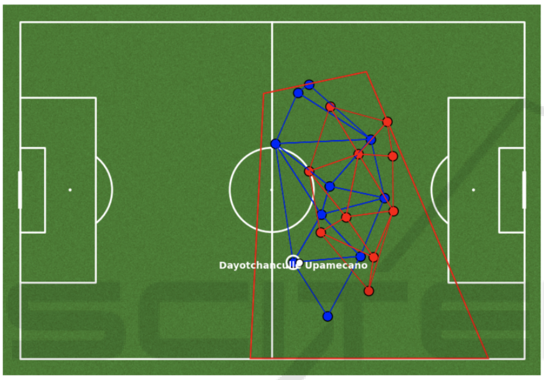

Figure 7: Support, contextual positioning of players, highlighting available passing lanes and supporting options.

Creativity

Creative actions introduce unpredictability through dribbles, disguised passes, or unusual movements. These actions break rigid defensive lines and surprise opponents (Rein and Memmert, 2016; Bauer and Anzer, 2021; Stival et al., 2023).

We track the number of successful creative actions, J_s by:

$$J_s = \sum_{i=1}^{n} J_i, \quad J_i = \begin{cases} 1 & \text{if creative action succeeds} \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

where J_i is a binary indicator function accounting if creative action i succeeded (or not).

The ground covered in these creative moments can be assessed by distance d_c:

$$d_c = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{21}$$

where x_1, y_1 and x_2, y_2 correspond to the start and end coordinates for the creative action.

As illustrated in the previous figures, rather than focusing purely on statistical metrics, the tool is designed to represent how and where these tactical principles occur on the pitch. By combining event data with 360 freeze frames, it becomes possible to explore the spatial context of each action, including the positioning of teammates, opponents, and the visible area perceived by the player at the time of the event.

Notably, the use of timestamped notational data enables the clear definition of time boundaries for the representation of each principle of play. In Figure 8 different metrics are represented at the two time boundaries of the selected event (a pass).

The aim is to go beyond isolated data points and enable the analysis of movement, positioning, and interaction patterns within the collective behaviour of the team. The system helps identify when certain principles are respected or broken, and under what match conditions these patterns tend to emerge, offering valuable support for tactical evaluation and coaching decision-making.

5 CONCLUSIONS

Building upon the review of existing tools, this paper examined the evolution of soccer data visualisation, pointing out the transition from static statistical outputs to more sophisticated, context-aware systems. While the field has advanced considerably, many existing tools still fall short in representing the tactical nuances of the match—particularly those related to the principles of play that guide collective team behaviour.

To address these limitations, we developed a visualisation prototype based on StatsBomb Open Data, designed to capture and interpret tactical patterns such as compactness, pressing, width, support, and penetration. The tool integrates spatial and temporal context using event data and 360 freeze frames, allowing analysts to explore not just what happens on the pitch, but how and why those behaviours emerge in different phases of play.

Rather than relying on isolated metrics or predefined statistics, the system visualizes the positioning, interactions, and movements that underpin team dynamics. This enables analysts and coaches to evaluate whether tactical principles are being respected, where they break down, and under what match conditions such patterns tend to appear.

Match-related factors such as opponent, score, referee and lineups are integrated as contextual information and can be used to filter or group the visualisations. This allows analyses across multiple matches,

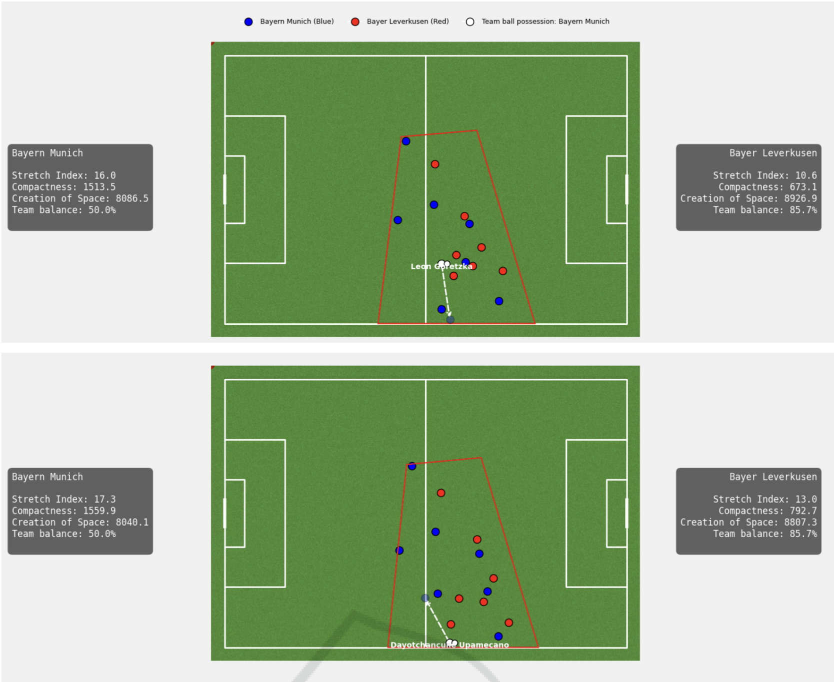

Figure 8: Two consecutive moments.

for example by aggregating positional data to build heatmaps or computing average metrics for specific opponents, score-lines or lineups.

The tool has been developed in close collaboration with an elite-level coach, who provides continuous expert feedback as a form of practical validation.

Ultimately, the approach bridges the gap between raw match data and applied tactical insight, offering a practical resource for those seeking to enhance performance evaluation, coaching feedback, and decision-making in professional soccer. Although using StatsBomb open data the principles and tools proposed are of general validity and can be used, with proper adaptation and caution, to other data sets.

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