Phase III: Quantifying the "Link Player" in Soccer: A Network and Spatial Analysis

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Executive Summary

In soccer, certain players operate as "link players," seamlessly connecting the team's defensive, midfield, and attacking units. Their influence often goes unnoticed because traditional metrics focus on more conspicuous actions such as goals, tackles, or assists. By integrating network and spatial analyses, this study introduces a framework to identify and quantify the subtle but pivotal contributions of these link players.

Using Hudl StatsBomb's Bayer Leverkusen "Invincibles" dataset from the 2023/24 season, the project leverages event-level data and positional information of all on-field players to create dynamic passing networks and spatial partitions of the pitch. Network metrics—such as degree centrality, prestige (weighted in-degree), and network density—reveal a player's involvement in passing sequences, highlighting whether they serve as crucial hubs or reliable outlets in ball circulation. Spatial analysis through Voronoi diagrams adds another dimension, illustrating the areas of the field each player controls or can influence at critical passing moments.

Additionally, passes are evaluated on their direction and progression toward the opposing goal. This allows the introduction of a composite metric, "Pass Voronoi Efficiency," which combines spatial dominance, passing volume, and forward progression. By correlating these metrics with outcomes like shots and goals, we move beyond traditional statistics to a model that illuminates how certain players function as connective tissue, maintaining possessions, advancing play, and enabling the team's tactical objectives.

The results demonstrate that players like Granit Xhaka, Exequiel Palacios, and Florian Wirtz play central linking roles, consistently appearing in the build-up to shots and helping the team maintain both possession stability and territorial advantage. While some players excel in controlling large spatial areas, others show a greater capacity to use their positioning and ball progression to unlock scoring opportunities. These findings empower coaches, analysts, and scouts to make more informed decisions about player development, tactical planning, and in-game adjustments.

This modeling framework offers a new lens through which to understand and value the hidden influences in a team's structure. By capturing the essence of linking play—network connectivity, spatial awareness, and forward-oriented passing—this approach enhances the traditional soccer analysis toolkit, supporting more nuanced player evaluations and strategic insights.

Business Understanding

In the dynamic game of soccer, the flow of play and the transition from defense to attack hinged on players who link the team together. These players served as the connective tissue of a team, facilitating movement, maintaining possession, and creating opportunities by seamlessly integrating separate phases of play. Traditional statistics often focused on prominent actions such as goals or tackles, unintentionally neglecting the subtle yet vital contributions of a player who helped facilitate the play together. The absence of specific metrics to evaluate these players presented a challenge for teams aiming to identify and develop such talent. Recognizing and quantifying the influence of link players offered several benefits, including enhanced tactical decision-making, improved player development strategies, and more effective scouting processes. This project utilizes network analysis and spatial dynamics to create comprehensive metrics that captured the essence of a link player's impact on the game.

Network metrics like degree centrality and degree of prestige were used to evaluate a player's role within the team's passing network. High centrality indicated frequent involvement in passing sequences, while high prestige reflects the trust teammates placed in the player as a passing target (Clemente et al., 2020; Leela et al., 2024; Caicedo-Parada et al., 2020). Network density, which measures the connectivity within the passing network, provides further insight into a player's influence in maintaining possession and facilitating play (Pina et al., 2017; Merlin et al., 2024). Voronoi diagrams were used to provide spatial analysis, showing how much space a player controlled and created for their teammates, indicating the quality of passes (Leela et al., 2024; Merlin et al., 2024). Each pass is measured in terms of its direction towards the attacking goal. Passes which travel more toward the goal were scored higher than passes the move horizontal or away from the goal. Integrating these networks and spatial metrics allows for a more comprehensive assessment of a player's ability to link play. This approach defines linking play not only by frequency of passes but also by their quality, distribution, and spatial effectiveness, allowing for a deeper understanding of how a player contributed to ball movement and play transitions.

Centrality metrics reveal whether a player's involvement in passing sequences correlated with successful attacks, such as goals and shots. Lower centrality often aligned with a player's crucial role in connecting the team's attacking efforts (Clemente et al., 2015; Pina et al., 2017). The analysis of passing sequences using adjacency matrices allowed us to track individual players' contributions to build-up plays that led to shots or goals (Clemente et al., 2015; Caicedo-Parada et al., 2020). These techniques provided a multi-dimensional assessment of how link players influenced team success. By evaluating their role in passing networks, pass quality, and offensive build-up, we could correlate their performance with key outcomes like goal creation, team cohesion, and overall match success. Network metrics can be especially useful for helping coaches and players understand team dynamics and to aid in decision making when trying to improve training and match analysis (Clemente et al., 2015). Using passing networks, important players can be extracted based on the possibility of the pass or the covering between players. (Takahashi, 2017). Additionally spatial temporal data can help to understand the effects of situational variables, opposition team formation, and playing position on running performance and network analysis (Aquino et al, 2020).

Data Understanding and Preparation

The project utilized Hudl StatsBomb's Bayer Leverkusen Invincibles Season data. This dataset has Hudl StatsBomb's standard event data and 360 tactical data for all thirty-four of Bayer Leverkusen's league matches in 2023/24. With around 3400 events per game, as well as the locations of all players in the visible frame around each event this data has all the data components to complete the project.

Via the blog post from Hudl StatsBomb's,

> [Bayer Leverkusen] were excellent at both ends of the pitch, with the 2nd-best open play expected goals (xG) created and best open play xG conceded, and were the most territorially-dominant team in the league too, progressing the ball to the final third most often while allowing their opponents into the final third least often.
>
> They achieved this without employing an overly aggressive press but whilst maintaining the highest defensive line in the league -- their success was built not on overwhelming the opponent with hard-running and aggression, but through intelligent positioning and coordinated pressing traps.

One advantage of this dataset is its public availability. It also contains all of the data necessary to create a minimum viable product. The disadvantages are that any model created with just this data will be heavily biased to the characteristics of Bayer Leverkusen.

Narrowing down the 161 columns in the dataset was vital for focusing on the scope of the project. The following variable table contains all of the necessary variables that were used in the project.

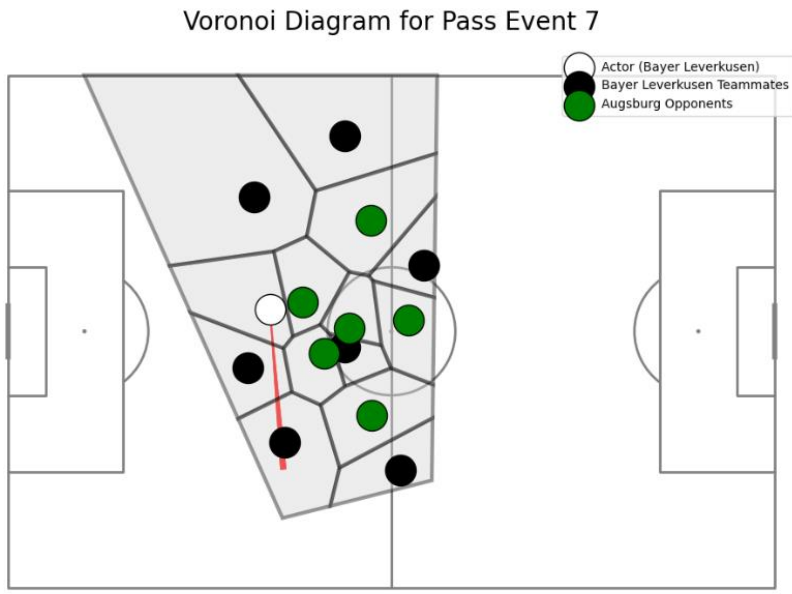
Variable Table 1

Variable Name	**Definition**	**Relationship to Research**	**Variable Dataframe**
id	uuid – The unique identifier for each event.	Used to iterate through the events	events_df
index	Integer – Sequence notation for the ordering of events within each match.	The order of events.	events_df
period	integer – The part of the match the timestamp relates to (1 – first half, 2 – second half.)	Period of the events	events_df
timestamp	Timestamp - Time in the match the event takes place, recorded to the millisecond.	Time of an event is important for defining when passing sequences occur.	events_df
type	object – id / name of the event type. For example, 42 / "Ball Receipt": The receipt or intended receipt of a pass.	The type of event is important for selecting passing, shooting, and goal events.	events_df

possession	integer - Indicates the current unique possession in the game. A single possession denotes a period of play in which the ball is in play and a single team is in control of the ball. New possession is triggered after a team demonstrate they've established control of the ball. A new possession can begin even if the same team has possession of the ball for example, a blocked pass goes out for a throw in for the same team, this would be a new possession for the same attacking team.	Important for knowing when a passing sequence ends. Knowing the beginning and end of a passing sequence allows for the building of network graphs which we can compare.	events_df
possession_team	object - integer. The ID of the team that started this possession in control of the ball. Note that this will appear even in opposition events like tackles attempted during the possession. e.g., 1 / "Arsenal"	The team in possession helps to separate the passing sequences of teams. This allows for building network graphs.	events_df
team	object - Id / Name of the team this event relates to. Team object will only display if the event is tied to a specific team. e.g., 1 / “Arsenal”	Knowing the specific team is useful for separating events in a match and creating readable visualizations.	events_df
player	object - Id / Name of the player this event relates to (player object will only display if the event is	Knowing the player involved in an event is useful for identifying effective link players.	events_df

	tied to a specific player). e.g., 5079 / "Zlatan Ibrahimovic"		
location	array [x, y] - Array containing two integer values. These are the x and y coordinates of the event (this only displays if the event has pitch coordinates). e.g., the center of the field is (60,40)	The location allows for the creation of Voronoi diagrams.	events_df
off_camera	Boolean – The event occurred while the camera was off. Thus, data accuracy is not guaranteed, and information is logically inferred by collectors.	Events which happened off camera were avoided since the location of the players in these events is unknown.	events_df
pass	contains multiple nested data frames which all describe different attributes of a pass.	Passing is the primary method by which link players were analyzed.	events_df
shot	contains multiple nested data frames which all describe different attributes of a shot.	Shots were used to determine which possession to analyze further	events_df
event_uuid	UUID - The unique identifier for the event matching this freeze frame.	This connection was crucial for integrating temporal and spatial analyses. By matching events with their spatial context, we analyzed how a link player's actions correlate with player positioning and movement patterns on the field, enhancing our understanding of their role in linking play.	frames_df

visible_area	Array - An array of coordinates describing the polygon visible to the camera, from which the 360-freeze frame was collected. This shape makes it explicit which areas were visible. Player locations may be outside the visible area where these were manually placed. The format of the array is: X1 Y1 X2 Y2... Xn Yn X1 Y1, describing a closed loop around the visible area of the pitch. The visible area can also be empty where the camera was not on the pitch at the time the frame was collected.	Ensures that spatial metrics, such as Voronoi diagrams, accurately reflect the areas of the pitch where the player is operating. Since not every player is always visible, some areas may be bigger or smaller than others, but on average, they should represent the area in which a player receives the ball.	frames_df
freeze_frame	Array - Like shots, this is an array of freeze frame objects, similar to those described in the Events API spec. However, these freeze frames will not contain player identification, beyond their team (except for the player performing the current event who will be marked as the actor).	This spatial information is essential for constructing visual representations like Voronoi diagrams and for analyzing spatial relationships between players.	frames_df



Modeling

The data is represented by event level data, where each row of the dataset corresponds to a discrete on-ball action. Key event types include passes, carries, and shots. For each event, we record attributes such as player and team identifiers, spatiotemporal coordinates, event outcomes, and contextual game variables such as timestamps.

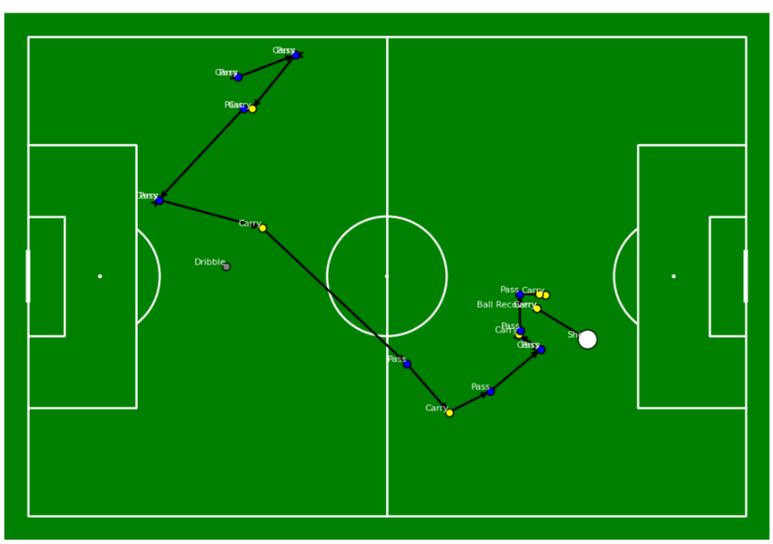
The passing behavior of teams and players is conceptualized as a directed graph (digraph), where each node represents a player, and each directed edge corresponds to one or more passes from one player to another. Each player active in each match forms a node. Players are identified by their unique names or IDs. A directed edge from node i (player i) to node j (player j) is established if player i attempts and completes a pass to player j. Edge weights represent the frequency of successful passes (pass volume) along that directed link. This weighted directed graph captures both the structure (who passes to whom) and the intensity (how often) of passing relationships.

Once the directed and weighted pass network is constructed, we compute standard network metrics to characterize individual players and the overall team structure. Degree Centrality measures a player's activity in the network (in-degree and out-degree centrality). Higher values suggest that a player is either a frequent passer (out-degree) or a key receiver (in-degree). Prestige (Weighted In-Degree) captures a player's importance in receiving possession. High prestige indicates a player often acts as a hub that others choose to pass to, potentially reflecting tactical roles such as link-up players or creative midfielders. Density measures the density and clustering characteristics of the passing network inform on how interconnected or centralized the team's passing structure is.

Beyond the topological structure of passing networks, we incorporate spatial modeling to understand how player positioning and visual availability shape passing decisions. At the time of each passing event, all players on the pitch are represented as points. Using their positions, we construct Voronoi polygons to partition the pitch into dominance areas: each polygon defines the region of the pitch closest to a particular player than to any other. Intersecting these polygons with the visible area of the passer (as determined by broadcast camera frames and any occlusion data available) helps identify which receiving options are spatially and visually available. The visible area is modeled as a polygon that approximates the region seen during the game's broadcast. For each player, we compute the mean area of their Voronoi region that falls within the passer's visible polygon at various passing events. We relate the spatial metrics (Voronoi areas) to passing outcomes (success rates, distances towards the goal) to develop composite efficiency metrics. For instance, we define a "Pass Voronoi Efficiency" measure that balances the spatial dominance areas with the player's ability to progress the ball towards the opponent's goal. While basic passing metrics (e.g., completion rates, pass frequency, progressive passing distance) provide insight, combining spatial and directional data can yield richer indicators of performance. To that end, we define a "Pass Voronoi Efficiency" metric that attempts to combine a player's spatial dominance (derived from Voronoi areas), ball progression capability, and passing workload:

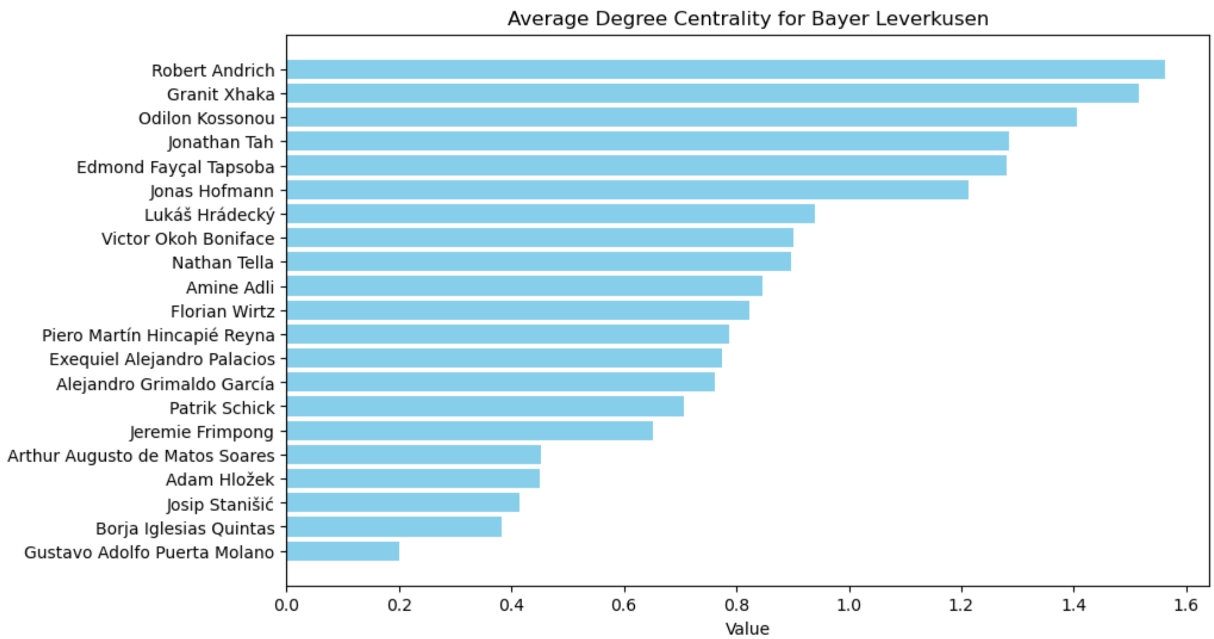
$$\text{Pass Voronoi Efficiency} = \frac{\text{Average Distance Towards Goal} \times \text{Pass Count}}{\text{Overall Average Area}}$$

By segmenting events into sequential possessions, especially those leading to key outcomes such as shots, we can analyze how team structure and player positioning evolve during critical offensive phases. This sequential modeling allows us to capture temporal patterns in ball progression and identify players who consistently appear as central hubs or critical space-openers at decisive moments. To achieve robust inferences, we aggregate results across multiple matches. By averaging event counts, network centrality measures, and spatial efficiency metrics over a range of fixtures, we derive player- and team-level performance indicators that are less sensitive to single-match variance. This longitudinal perspective supports more stable evaluations of player roles, playing styles, and tactical effectiveness.

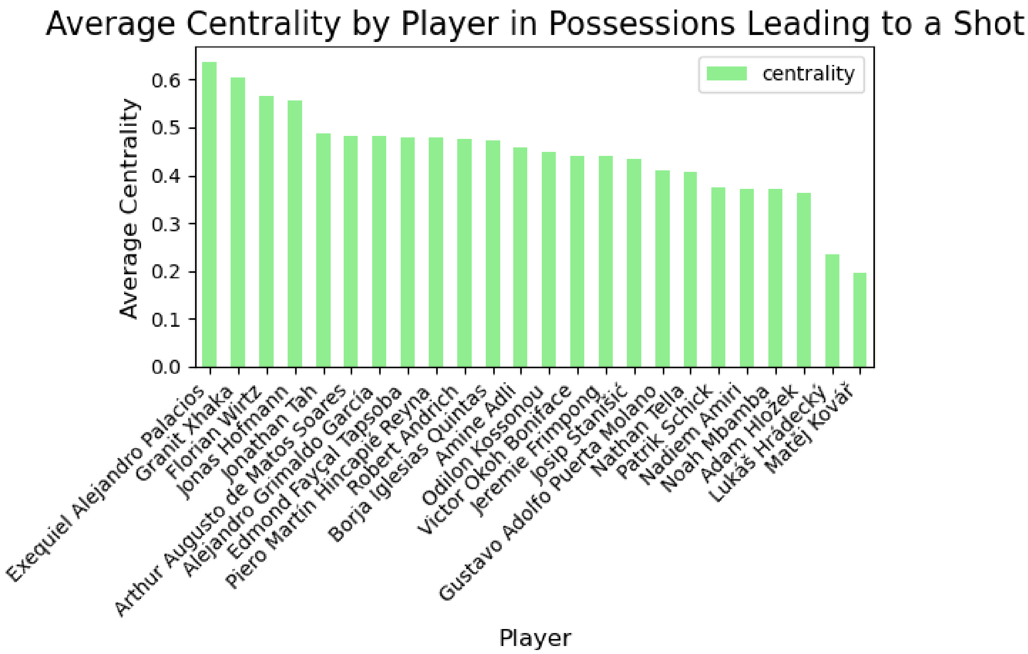


Evaluation

The degree centrality metrics and their corresponding visualizations highlight a clear hierarchy within Bayer Leverkusen's passing network. Players such as Robert Andrich, Granit Xhaka, Odilon Kossounou, and Jonathan Tah consistently rank highly in average degree centrality measures. These players function as crucial network hubs, either due to their tendency to receive and redistribute the ball frequently or their role as stable passing outlets.



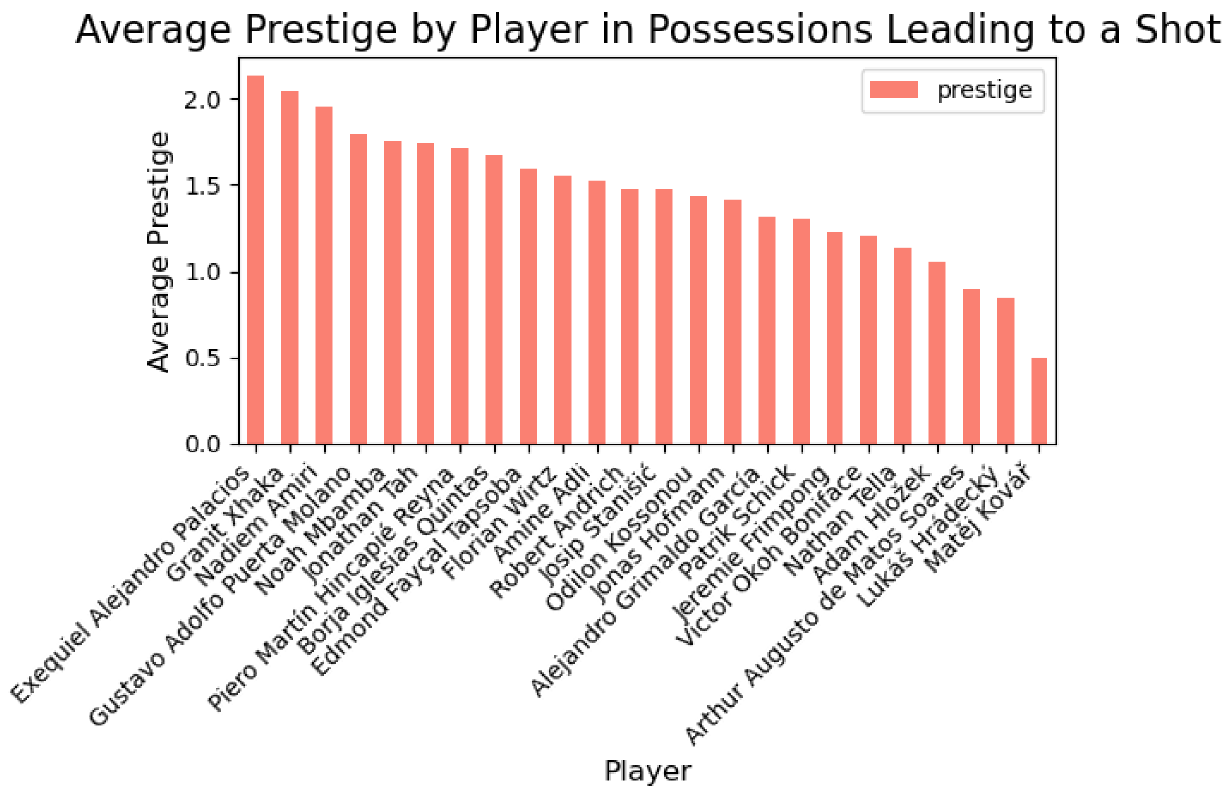
Xhaka and Palacios emerge as central figures in multiple contexts. High centrality in possessions leading to shots indicates that when the team constructs attacking moves, these players are integral links. They provide secure passing options, help maintain tempo, and effectively link defensive lines to attacking midfielders and forwards.



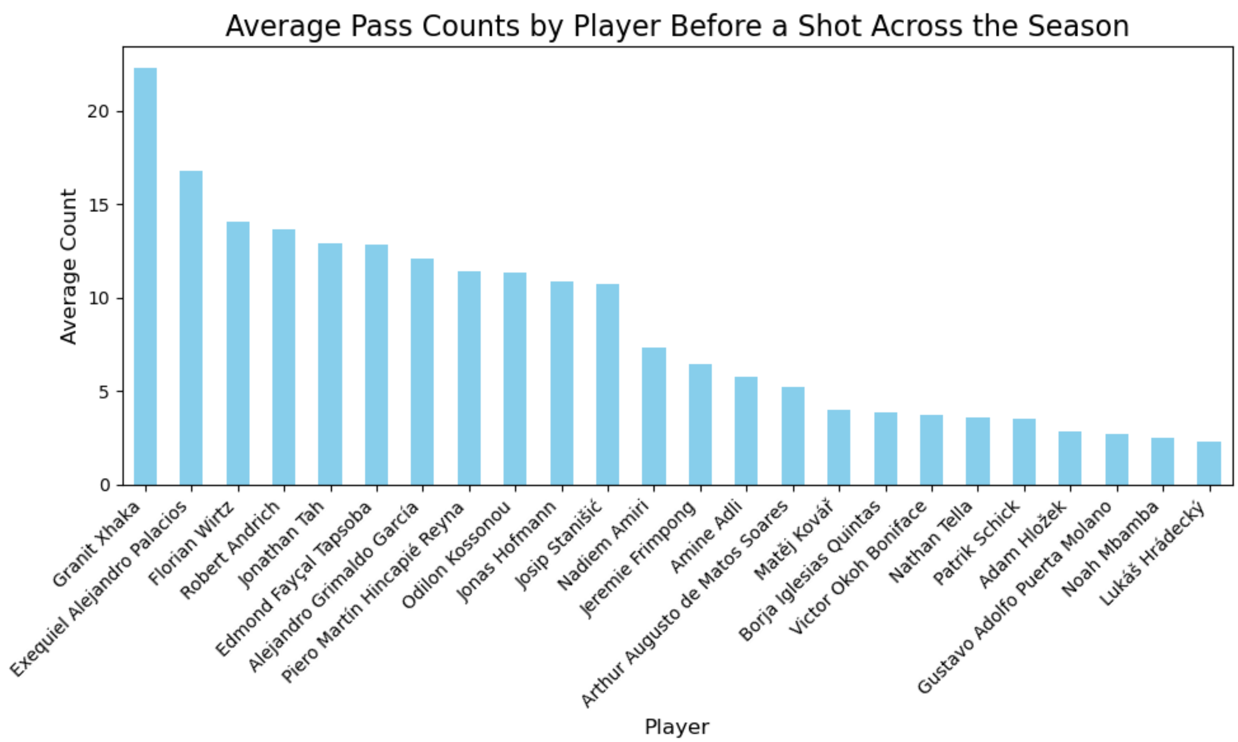
The tables summarize passing statistics—such as successful passes, total passes, and passes per minute—underscore the reliability and volume of involvement for certain midfielders and defenders. High success percentages from players like Granit Xhaka, Exequiel Palacios, and Jonathan Tah point to their technical proficiency and importance in maintaining possession. Their elevated passes-per-minute ratios and high completion percentages signal their capacity to orchestrate play and serve as safe conduits through which the team can cycle the ball.

player	successful_passes	total_passes	passes_per_minute	success_percentage
Granit Xhaka	85.0	91.3	2.0	92.7
Exequiel Alejandro Palacios	71.5	76.6	1.7	93.0
Jonathan Tah	59.3	61.8	1.3	95.8
Edmond Fayçal Tapsoba	56.9	61.4	1.5	91.0
Odilon Kossonou	51.3	55.3	1.2	92.4
Robert Andrich	44.8	49.0	1.3	92.8
Florian Wirtz	43.8	51.2	1.2	85.0
Piero Martín Hincapié Reyna	43.3	46.5	1.2	91.4
Josip Stanišić	41.5	45.3	1.2	91.2
Alejandro Grimaldo García	41.4	50.0	1.1	82.8

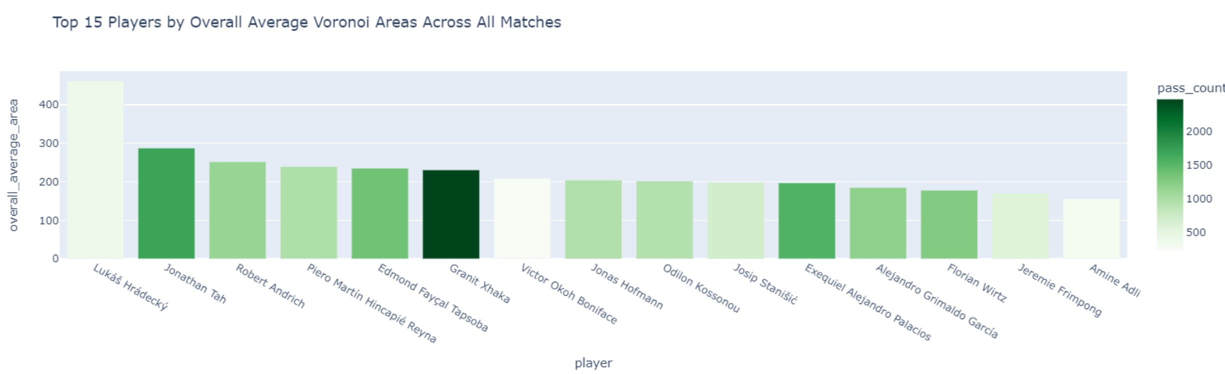
Focusing on possessions culminating in a shot, players like Palacios, Wirtz, and Xhaka appear consistently among the top performers in both centrality and prestige. Prestige, defined as weighted in-degree passes, highlights those who are frequently targeted when the team advances towards goal. The elevated prestige values for these players in shot-leading possessions emphasize their role as creative fulcrums who attract the ball at critical moments, assisting in final-third penetration and shot generation.



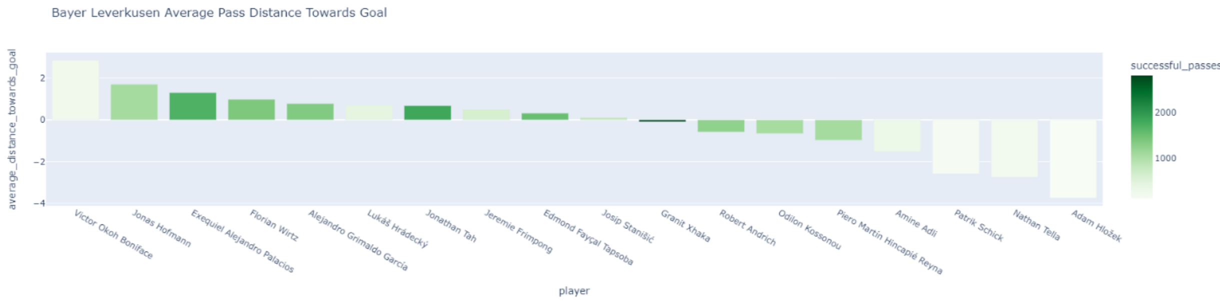
Granit Xhaka, notably, stands out not only in overall passing metrics but also in how often he is involved prior to a shot. High average pass counts before a shot, combined with strong success rates, reiterate his role as a primary orchestrator in the team’s build-up play. Similarly, Florian Wirtz’s prominence indicates a creative, forward-facing role, connecting deeper build-up to the final attacking moves.



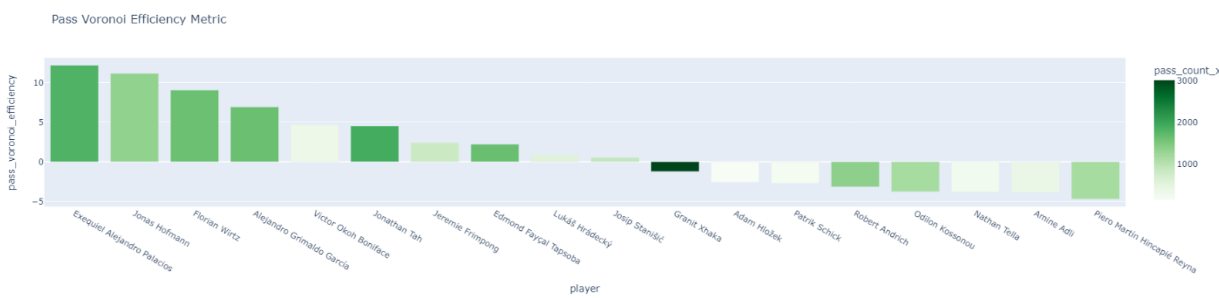
The introduction of Voronoi tessellations into the analysis adds a spatial dimension to the interpretation. The top fifteen players by overall average Voronoi area highlight, in some cases, individuals like Lukáš Hrádecký (the goalkeeper) who naturally command large uncontested spaces. Defenders and midfielders with substantial Voronoi areas, such as Jonathan Tah or Robert Andrich, may have more control of the pitch in terms of spatial dominance but must be evaluated in conjunction with how effectively they utilize this space.



The average pass distance towards the opponent’s goal differentiates between players who maintain possession laterally or backwards versus those who consistently seek forward penetration. For instance, Victor Okoh Boniface and Jonas Hofmann’s positive forward distance suggests they serve as catalysts for vertical transitions, moving the ball into more dangerous areas.



The “Pass Voronoi Efficiency” metric precisely provides this combined lens. It balances a player’s ability to push the ball towards goal, their passing volume, and the spatial advantages they hold. Players like Exequiel Palacios and Jonas Hofmann show high positive values, suggesting not only do they secure meaningful areas on the pitch, but they also convert this spatial control into forward-looking passing patterns that help progress the play closer to the opponent’s goal. Conversely, players who have large Voronoi areas, but lower positive ball progression may score less favorably, indicating a disconnect between spatial dominance and forward ball movement. This discrepancy can inform tactical adjustments or player role refinements, encouraging certain players to leverage their spatial advantage more aggressively to move the play up field.



When overlaid with their network metrics and Voronoi measures, a pattern emerges in which certain players contribute not only to possession stability and safe passing but also to territorial gains. Players who excel in this dimension may be considered key contributors to the team’s attacking identity and a source of breakthrough passes that create scoring opportunities.

Solution Deployment

The solution deployment phase transforms the analytical framework into an operational system that seamlessly integrates into Bayer Leverkusen's existing infrastructure. To ensure automated and reliable data processing, the system connects directly to StatsBomb's APIs and the club's internal tracking systems, enabling real-time ingestion of match data after each game. Computationally intensive tasks, such as generating Voronoi tessellations and calculating network metrics, are executed within a scalable computing environment using cloud-based solutions or local clusters. Results are stored in a structured database (e.g., PostgreSQL) and integrated into existing analytics platforms, such as Tableau or Power BI. This enables seamless retrieval and visualization of insights, ensuring technical and non-technical users can access key findings efficiently. Interactive web dashboards and custom reporting templates provide tailored outputs for different stakeholders, including coaches and analysts, who can filter metrics like centrality, prestige, and pass Voronoi efficiency by player, match, or possession sequences.

To enhance user accessibility, dynamic visualizations are paired with synchronized match footage, allowing coaching staff to analyze metrics alongside video replays of critical game sequences. This integration bridges the gap between quantitative insights and on-field tactical decision-making, making the findings actionable in both training sessions and match preparations. Additionally, models are periodically updated with new match data and recalibrated to account for changes in formations, tactics, or player roles, ensuring their continued relevance and reliability over time.

Discussion

This study presents a modeling framework that integrates network analysis, spatial Voronoi metrics, and a novel Pass Voronoi Efficiency measure to analyze passing dynamics, player influence, and ball progression within Bayer Leverkusen's performances during the 2023/2024 Bundesliga season. The results validate established tactical roles and also uncover areas for optimization in player contributions and team strategy. The network analysis highlights a clear structure within Bayer Leverkusen's passing system, where specific players—particularly Granit Xhaka, Exequiel Alejandro Palacios, and Jonathan Tah—emerge as central hubs. These players exhibit high degree centrality and prestige, indicating their importance as reliable receivers and distributors of the ball. This is particularly evident in possessions leading to shots, where Palacios and Xhaka consistently feature among the most central and prestigious players. Xhaka's role as a deep-lying playmaker ensures continuity and control in build-up phases, while Palacios and Florian Wirtz bridge the midfield to attack, facilitating goal-creating moves. The results reaffirm the importance of maintaining stability through core midfielders while recognizing that players like Palacios and Wirtz act as creative catalysts. This balance between possession retention and forward progression is crucial for Bayer Leverkusen's tactical identity. By combining spatial dominance and passing outcomes, the *Pass Voronoi Efficiency* metric offers a novel lens to evaluate player performance. Players such as *Exequiel Palacios* and *Jonas Hofmann* stand out as high performers, successfully balancing forward ball progression, measured by their ability to reduce the distance to the opponent's goal, and spatial utilization, by leveraging their available Voronoi areas to execute impactful passes. Interestingly, *Granit Xhaka*, despite his high centrality and success rates, scores relatively lower in pass Voronoi efficiency. This suggests that while Xhaka provides immense value in possession retention and distribution, his contributions tend to prioritize stability over forward thrust. Coaching staff could explore strategies to encourage players with large Voronoi areas but low efficiency to take on more progressive passing responsibilities. Tactical adjustments, such as positional rotations or attacking patterns, could unlock greater forward movements from deeper positions.

The accuracy of the Voronoi tessellation and visibility modeling depends on the precision of player tracking data and the completeness of event annotations. Any missing or noisy location data might affect the reliability of spatial metrics. Our modeling assumes that the fundamental tactical roles of players (e.g., central midfielder, winger) remain consistent across the analyzed matches. Player roles and formations may vary between games, necessitating caution in interpreting aggregated season-long metrics. The current modeling does not explicitly account for tactical instructions, defensive pressure, or psychological factors that can influence passing decisions. We focus on observed spatiotemporal distributions and event outcomes as proxies for underlying tactical strategies.

Extending Voronoi analysis to account for player motion and temporal changes during possessions would provide a more nuanced view of spatial influence. Integrating defensive metrics—such as pressing intensity, pass blocking, or defensive spatial control—would help contextualize passing efficiency and spatial dominance. Combining network and spatial metrics with machine learning models could predict key outcomes, such as shot probability, ball loss risk, or optimal passing options. Additionally, applying this framework across different leagues, teams, and playing styles could validate its robustness and generalizability.

Learning Implications

The modeling methods and results presented in this study carry several important implications for analysts, coaches, and players in the context of professional soccer.

From a coaching perspective, visualizing passing networks and spatial control through Voronoi diagrams aids in the education of players regarding their roles and responsibilities. Instead of relying solely on match footage or conventional pass completion percentages, the integrated models help players understand how their positioning, decision-making, and ball circulation patterns directly contribute to team objectives.

Individual player metrics derived from centrality, prestige, and pass Voronoi efficiency highlight not just whether a player is successful in passing, but how effectively they use space and forward movement. This layer of insight fosters targeted training interventions. For example, a defender who dominates a large Voronoi area but rarely passes forward can be encouraged—through drills and scenario-based training—to take calculated risks in moving the ball up field. Likewise, a midfielder with excellent centrality but low progressive metrics can work on timing and angles of passes to exploit spatial advantages and unlock opponent lines.

Conclusion

This study establishes a novel and integrative approach to understanding and quantifying the roles of link players in soccer. By combining network metrics, spatial partitioning with Voronoi diagrams, and forward-progressive passing metrics, we gain deeper insights into how certain individuals knit together the structure of a team's play. The analysis of Bayer Leverkusen's 2023/24 "Invincibles" season shows that top link players are not only frequent passers and receivers but also skilled at transforming spatial dominance into goals.

The findings highlight that a player’s true influence often transcends conventional metrics. Players who emerge as key hubs in passing networks or who command significant pitch territory through Voronoi dominance can serve as the backbone of a team’s tactical identity. Yet, their impact is fully realized when they leverage their spatial control to drive the ball forward, generating more promising attacking moves.

As a result, clubs can use these insights to sharpen scouting, refine player roles, and tailor training interventions. Encouraging players who excel in maintaining possession but rarely progress the ball to adopt more assertive passing patterns or identifying individuals best suited to serve as creative conduits, allows teams to adjust strategies more proactively. Moreover, the adaptability of the analytical framework makes it suitable for cross-comparison between matches, teams, and even leagues, ensuring its applicability to evolving tactical landscapes.

In conclusion, integrating network and spatial analyses offers a richer, more holistic perspective on player contributions. By unveiling the hidden link player, this study provides a toolset for modern soccer analysis, facilitating better-informed decision-making and optimizing team performance on the pitch.

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