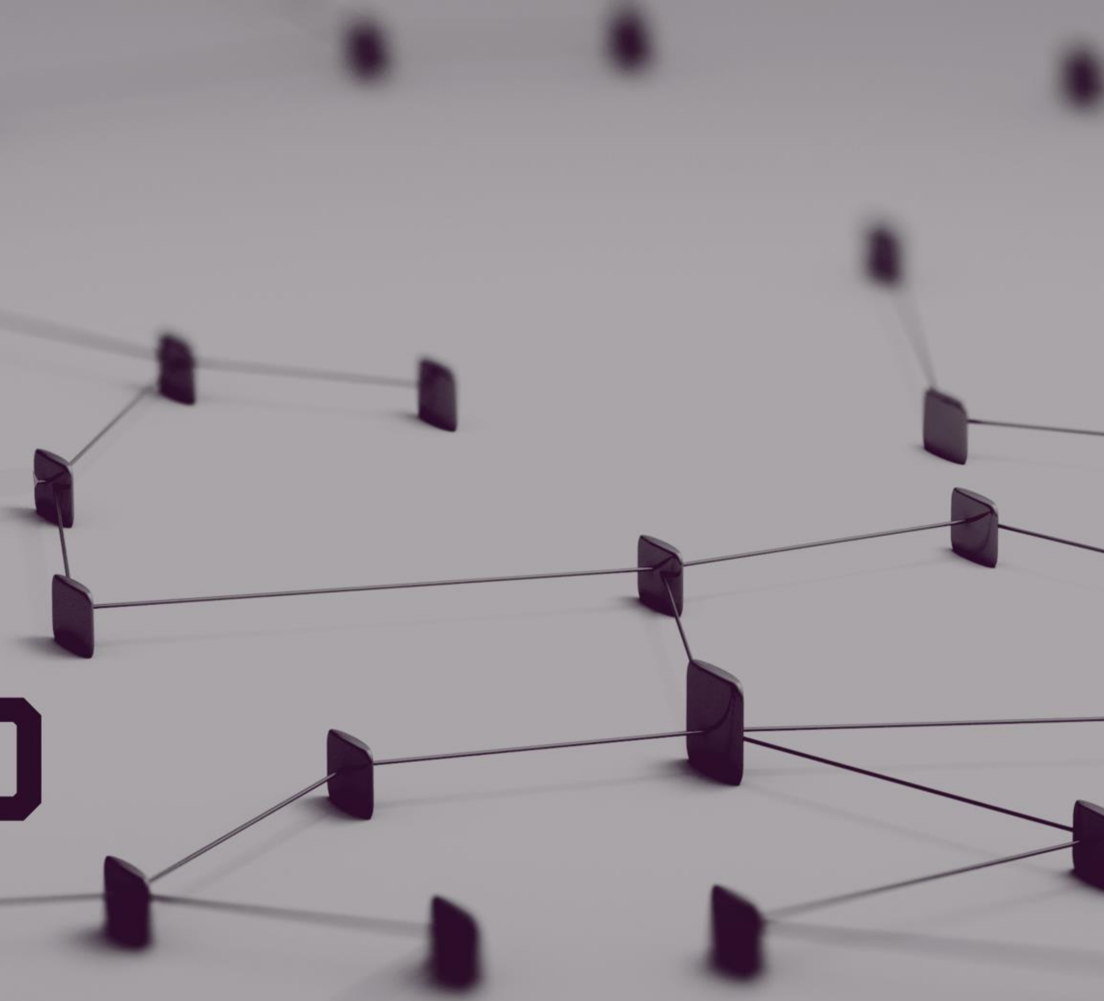
PORTFOLIO

Álex Fernández



Analytical Content

Throughout this document, a set of analyses are presented as a sample of the work I have carried out to date – although I am in a constant process of research and learning – both in my personal and educational projects as well as during my experience in the context of professional football.

Providing Value with Data through:

- **Context Analysis**
  - Metrics Evolution
  - Exploring Metrics and adding context through Visualization
- **Performance Analysis (Pre & Post-Match):**
  - Defensive Situations
  - Buildup
  - Chances Creation
  - Transitions
- **Recruitment Analysis | Scouting**
  - Advanced Metrics & Rankings
  - Performance Evaluation
  - Segmentation Processes: Squad's Game Model & Player Roles
  - Similarity Algorithms on Players and Teams
  - Recommendation / Matching Systems

Set of Presentation Tools

- **Specific Reports and Presentations**
- **Interactive Dashboards on Visualization Tools:**
  - Power BI
  - Tableau
  - Streamlit
- **Recurrent Reports:**
  - Detailed reports of players included in a shortlist
  - Pre-Game Reports: opposition analysis
  - Post-Game Performance Analysis
  - Monthly / Last-five-games Performance Report

Implementation Cases

- Detection of personal strengths to impact match preparation through the study of playing patterns in both the own team and the opponent.

- Monitoring the team's evolution in key phases of the game for the execution of the playing model, based on specific indicators – e.g., % of Immediate Recoveries after Loss by Zone.

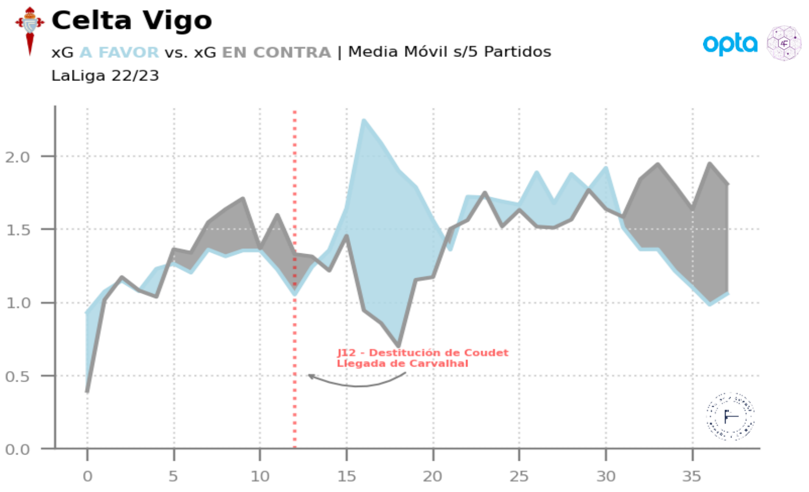
- Periodic identification of leaders, by competition and/or club, in specific metrics to feed and optimize the player tracking strategy or assess the team's performance in a particular area of interest.

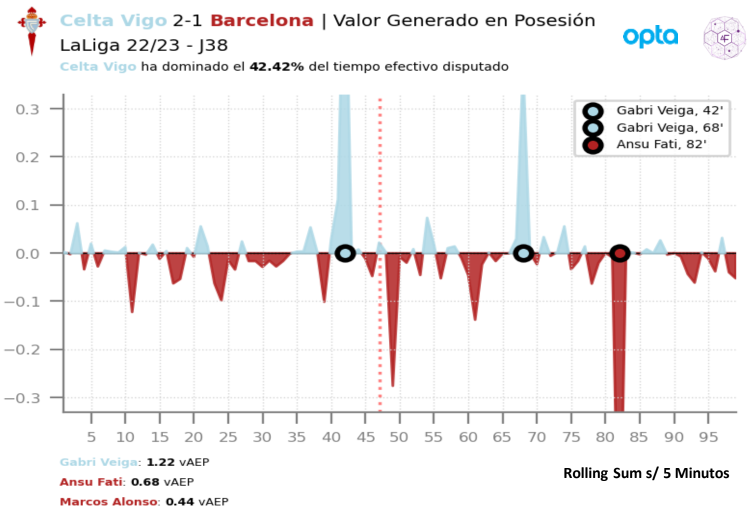
- Detailed reports on the aggregated performance of players who are targets in the market.

- Objective identification of attainable profiles that would match to a specific tactical context, positional role and game model, reducing uncertainty in player acquisitions.

- Acquisition of players who can replace a potential sale, approaching their level and at a minimal economic cost.

Context Analysis | *Metrics Evolution*





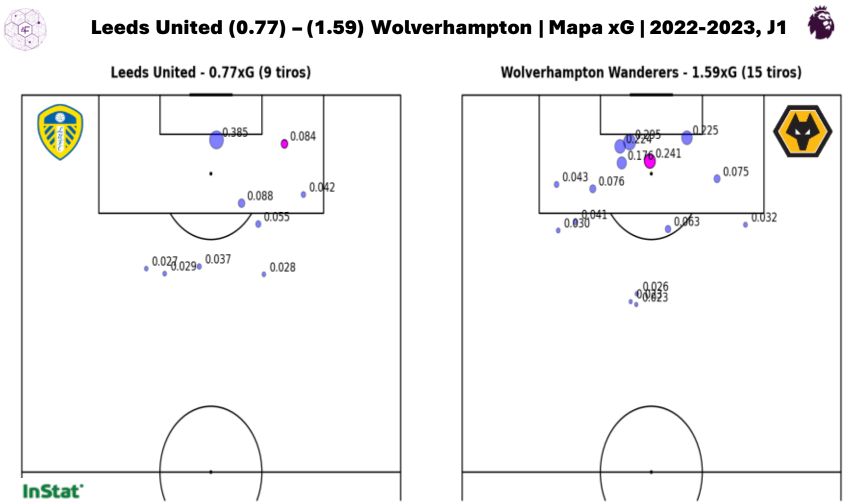
Long-Term Momentum Tendencies

It allows for establishing a comprehensive picture, either over a full season or, if desired, a longer period, regarding the team's sustained performance. This measurement is based on objective performance indicators – in this case, Expected Goals For vs. Against, contextualized through a moving average. With this type of globally focused analysis, the team's competitiveness can be measured based on what it produces on the field.

Match Momentum

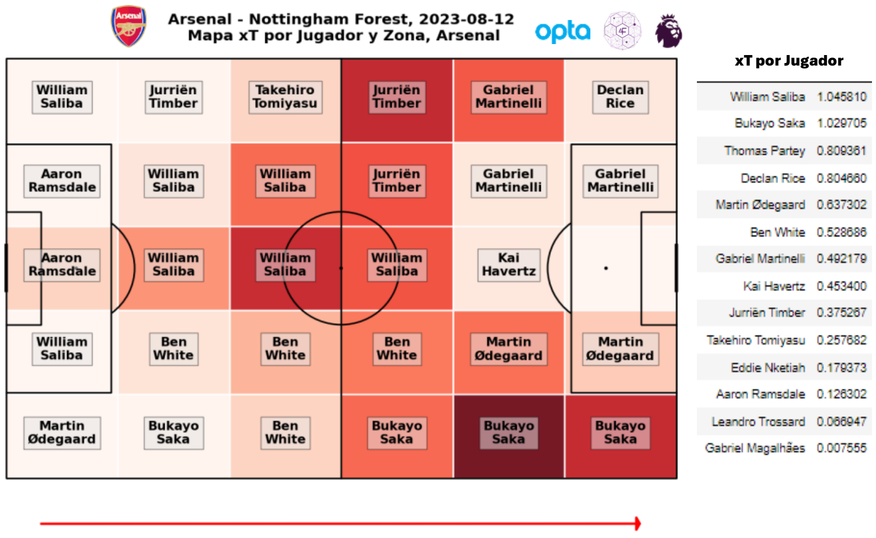
This diagram illustrates the flow of value generated with the ball throughout a match, based on the vAEP model. It provides an overall view of the dominance phases that have occurred during a match, as well as the level of control a specific team has needed to score. Additionally, it gives insight into which team has controlled the game, enabling conclusions and analyses that are separate from the final result.

Context Analysis | *Exploring Metrics: xG/xT*



xG Map

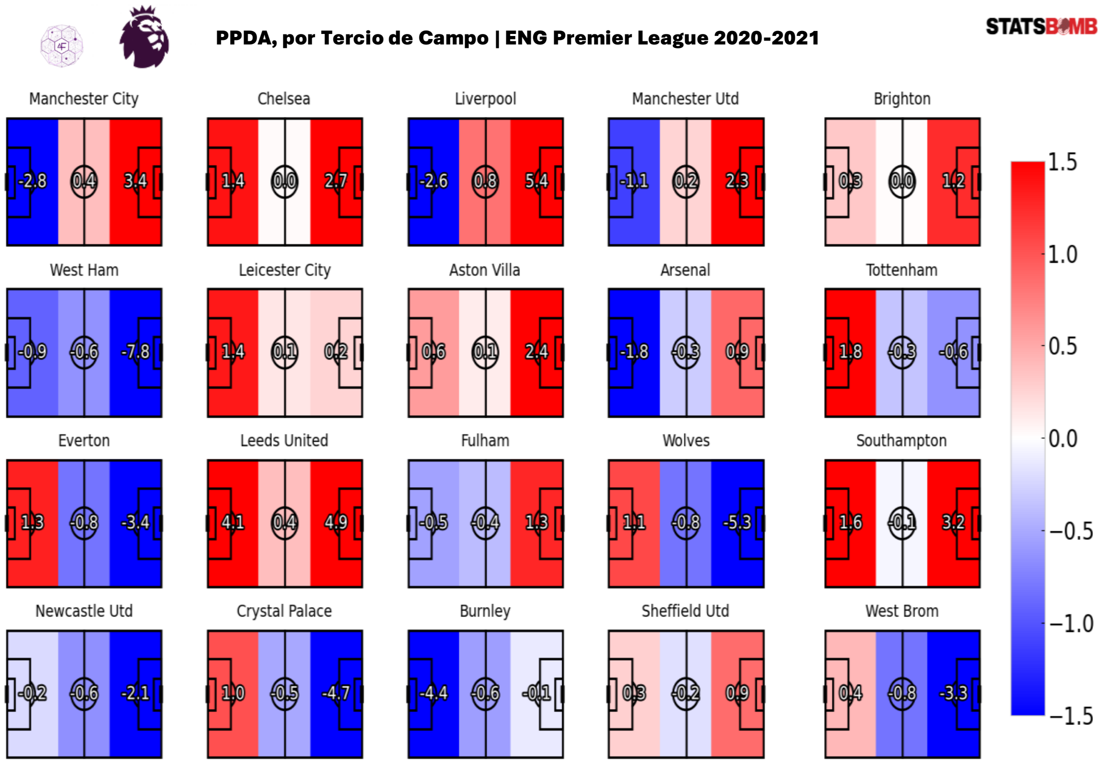
This visualization disposes on the field the specific location from which each shot is taken in a match, categorizing it based on the quality that the goal-scoring opportunity represents. To achieve this, an xG – Expected Goals – model is applied, which links, for each shot, a probability of ending in a goal based on its characteristics (zone, angle, striking surface).



On-Ball Value Added Heatmap

Expected Threat (xT) – based on the logic of xG – is one of several advanced indicators used to assign value to each action during a play based on its contribution to the team's likelihood of scoring in subsequent actions. This can result in the generation of a wide array of visualizations, among which we highlight this dominance visualization. In this visualization, we can observe which areas pose the most danger in a match and identify the player leading the team in that aspect.

Context Analysis | *Exploring Metrics: PPDA*

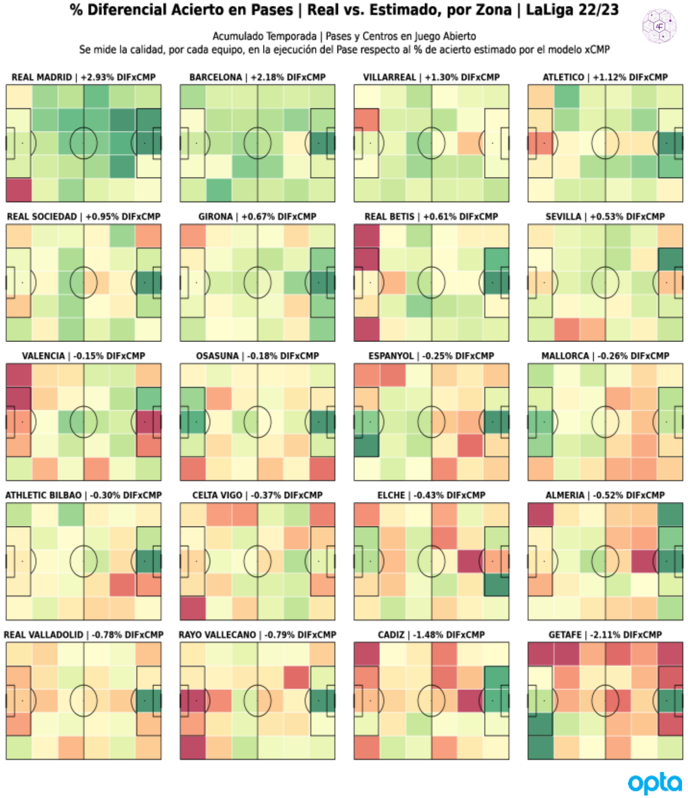


PPDA per Third

PPDA (Opposition Passes Allowed per Defensive Action) stands out as one of the most explanatory indicators of defensive intensity. Rather than merely recording pressures, it encompasses all kinds of off-ball actions with the purpose of regaining possession.

In this visualization, the differential of passes allowed by each team compared to the league average is displayed by thirds of the field. It's important to note that the color red and a positive indicator (>0) signify greater off-ball aggression.

Context Analysis | *Exploring Metrics: xPass*



DAP - Diferencial (%) de Acierto en Pases s/xCMP
Top 15 | LaLiga 22/23

Jugador	Minutos	N. Pases	xPass%	DAP%*
Matija Nastasic	988	298	75.9	5.15
Rodrygo	2591	1050	83.4	4.988
Toni Kroos	2320	2482	86.7	4.837
Frenkie de Jong	2716	2320	86.2	4.408
Andoni Gorosabel	1858	1049	80.4	4.403
Aitor Paredes	947	521	85.0	4.384
Martin Valjent	2888	1123	75.9	4.167
Axel Witsel	2473	1328	88.9	4.104
Mario Hermoso	2260	1515	82.9	4.042
Eric García	1545	1257	87.3	4.034
Igor Zubeldia	2767	1557	81.9	4.023
Lisandro Magallán	997	391	80.2	3.958
Aurélien Tchouaméni	2282	1700	89.3	3.871
Aïssa Mandi	1601	911	87.0	3.777
Andreas Christensen	1887	1507	90.4	3.761

Jugadores de Campo | Normalizado por 90 Minutos
Pases y Centros en Juego Abierto
+900 Minutos

opta

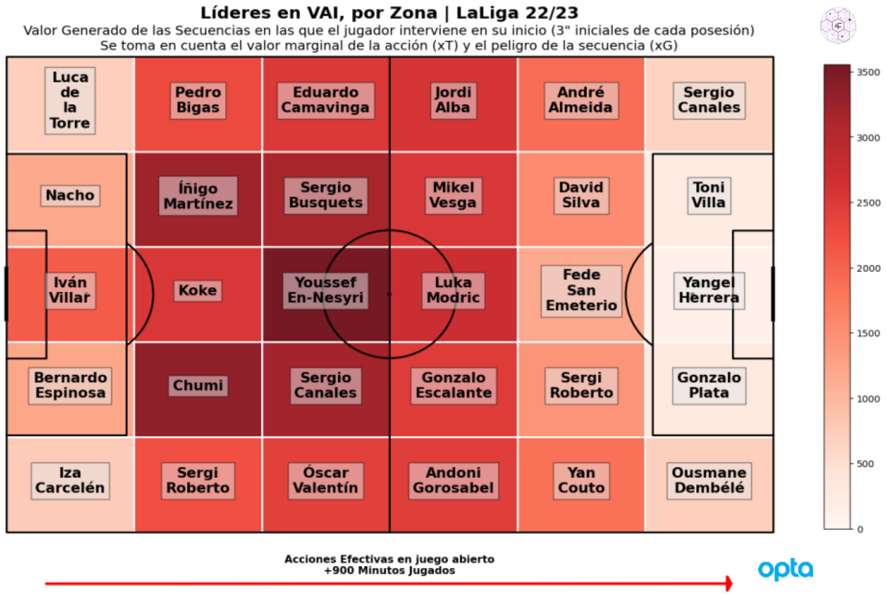
Pass Completion Models (xPass)

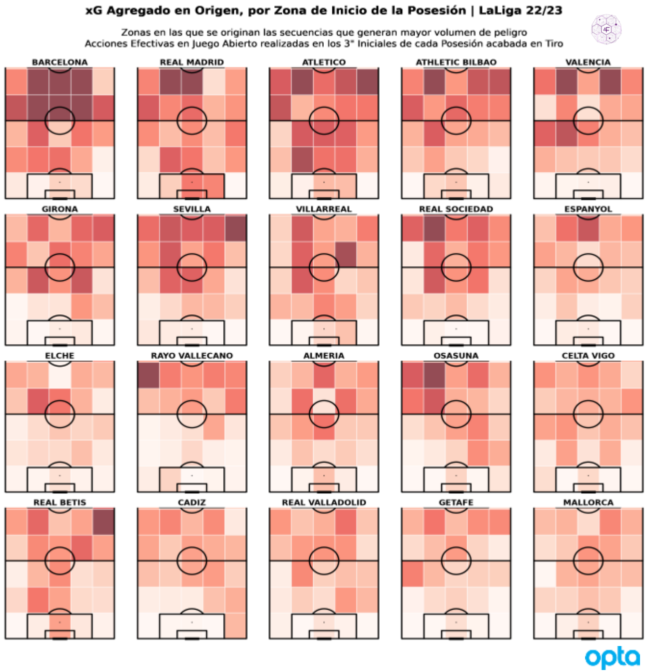
We understand the **xPass** – as Statsbomb names it – as the indicator that defines the probability of a pass being completed and received by a teammate. Additionally, it provides information on the value that this pass contributes to a specific possession.

The xPass model calculates the probability of success based on a set of variables derived from event data: position, distance, and angle of the pass's start and end, pass type (center, long/short, deep, set-piece, or moving), body surface involved, and time elapsed since the previous event.

To analyze and interpret this indicator, among other subsidiary metrics, we can find DAP (Differential of Accuracy in Passes), which compares a player's actual success rate with what the xPass model predicts. On the left, we display the differential by zone for each LaLiga team in the 2022/23 season; and on the right, the player ranking. As we can observe, Matija Nastasic succeeds in 5.15% more passes than expected based on the characteristics of those passes. Two of the world's leading figures in positional play, Toni Kroos and Frenkie de Jong, are prominently featured. Additionally, the indicator for Rodrygo Goes is noteworthy, achieving significantly higher accuracy than predicted, especially when intervening in advanced areas of the field.

Performance Analysis | *Exploring Metrics: VAI*

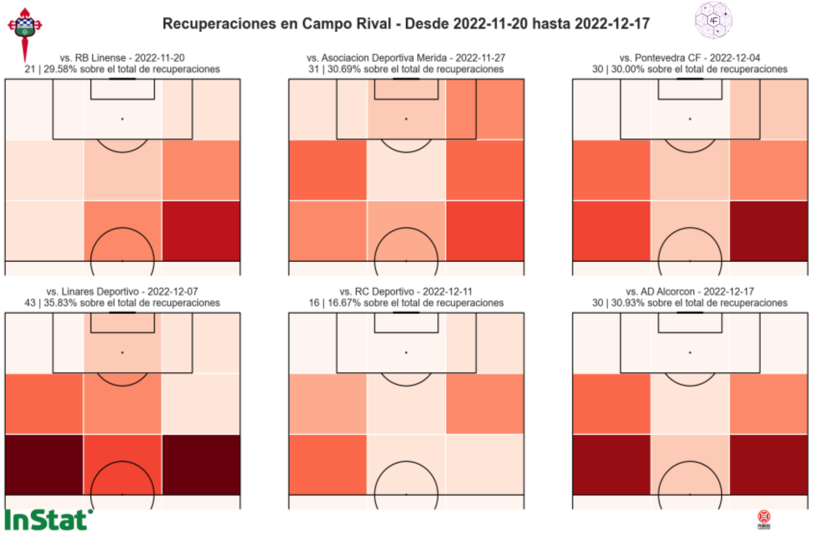


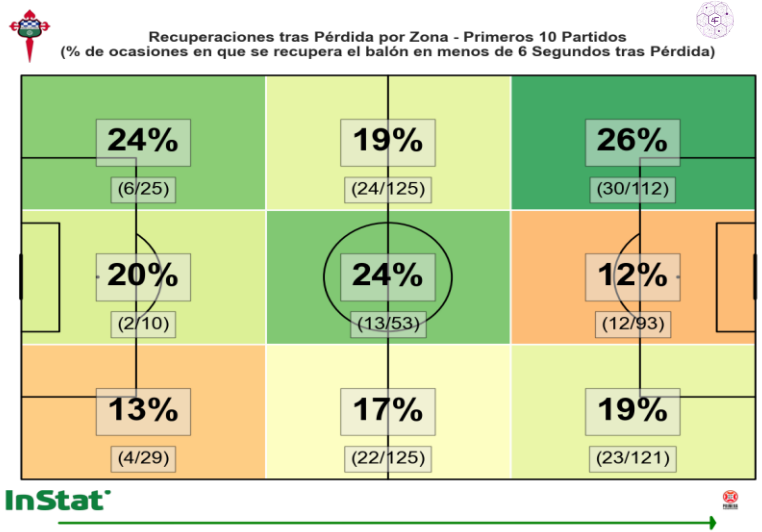


Value Added on Buildup Initiation (VAI)

This indicator explores the player's ability to create dangerous situations in the initial moments of possessions - the first 3 seconds. The calculation takes into account both the individual value contributed in the beginning of the sequence and the quality of the goal-scoring opportunity ultimately generated – xG. Illustrated on a field diagram, as shown in the left visualization, we can understand, for each zone of the field, which player leads in this indicator within LaLiga 22/23. Simultaneously, on the right, we see the zones where each team in the league originates sequences that create the highest-value scoring opportunities.

Performance Analysis | *Defensive Situations*





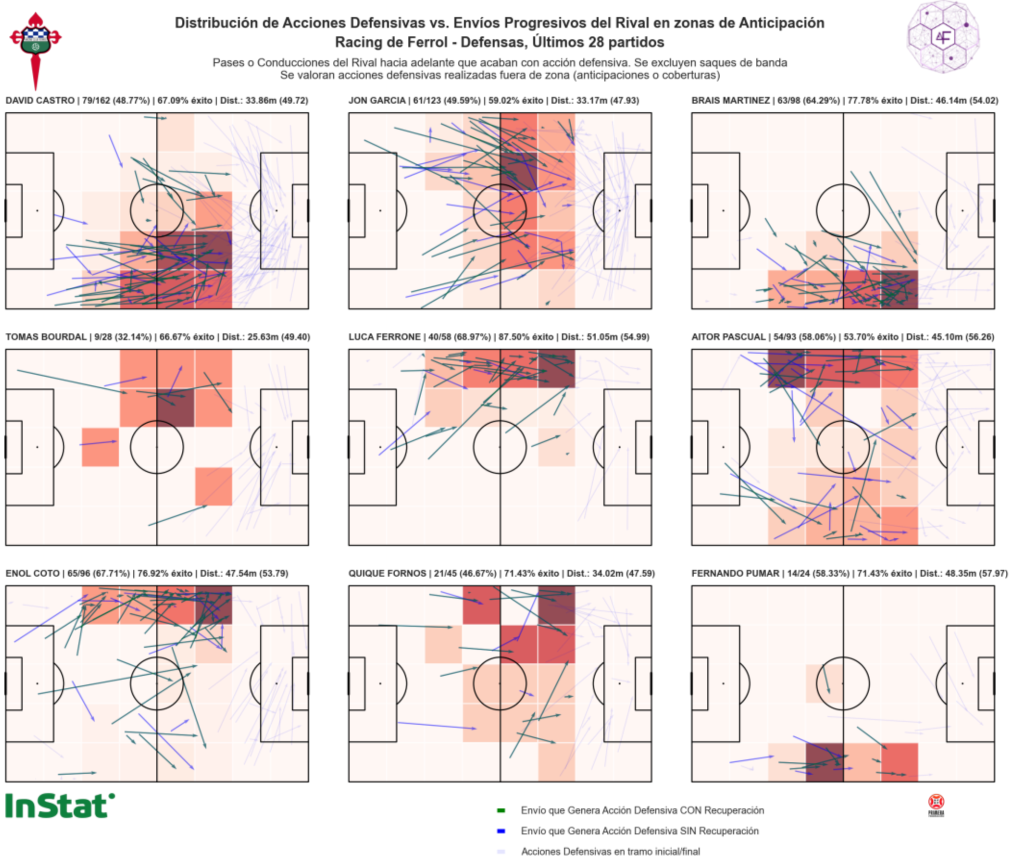
High-Recovering Areas

Through this visualization, we can locate the set of potentially dangerous recoveries – in favor of the team performing them – measuring their total volume and distribution across the entire opponent's field. In this case, instead of placing the actions at an aggregated level, various campograms are used to represent the last six games. This allows us to observe the differences based on the opponent.

Inmediate Pressure Efficiency

It is crucial for teams that seek to take the initiative and are aggressive in pressure after losing the ball to measure and understand how frequently they quickly recover the ball after losing it. By dividing the field into nine zones, the percentage of occasions when the ball is recovered within six seconds of the loss is displayed. The total number of losses and recoveries recorded is provided in parentheses.

Performance Analysis | *Defensive Situations*

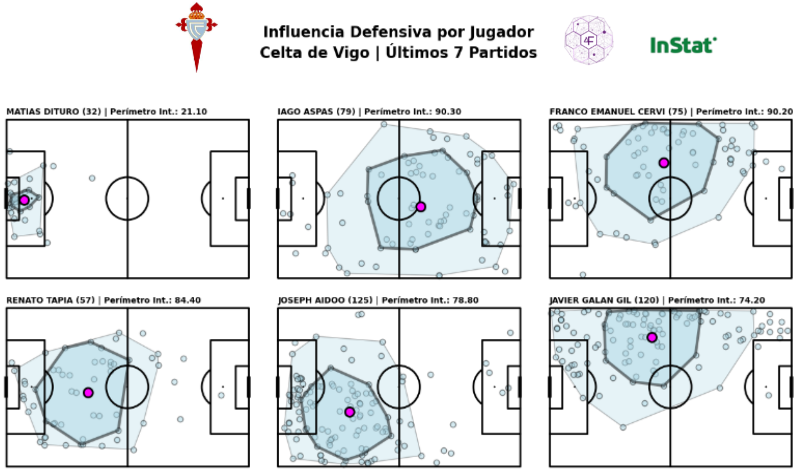


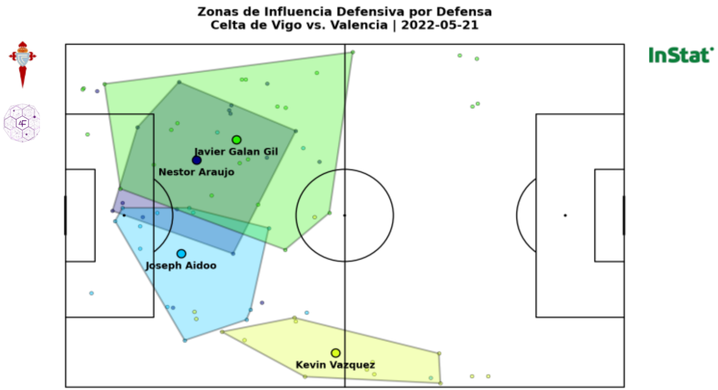
Anticipation Actions

This visualization aims to illustrate the volume and effectiveness associated with anticipatory defensive actions, specifically those performed in response to frontal/progressive passes from the opponent in a relatively advanced area. In these cases, the defender must leave their defensive position to anticipate and execute an interception or challenge.

Accounting the frequency of such actions and their typical locations, per player, helps discern the roles established among defenders – for instance, identifying which center-back tends to hold position and which one seeks to anticipate. This information is crucial for efficiently designing the game plan. Similarly, understanding the success rate – whether such defensive action results in a possession recovery for the team – influences match preparation and decision-making, whether the analysis is conducted for the own team or the opponent.

Performance Analysis | *Defensive Situations*





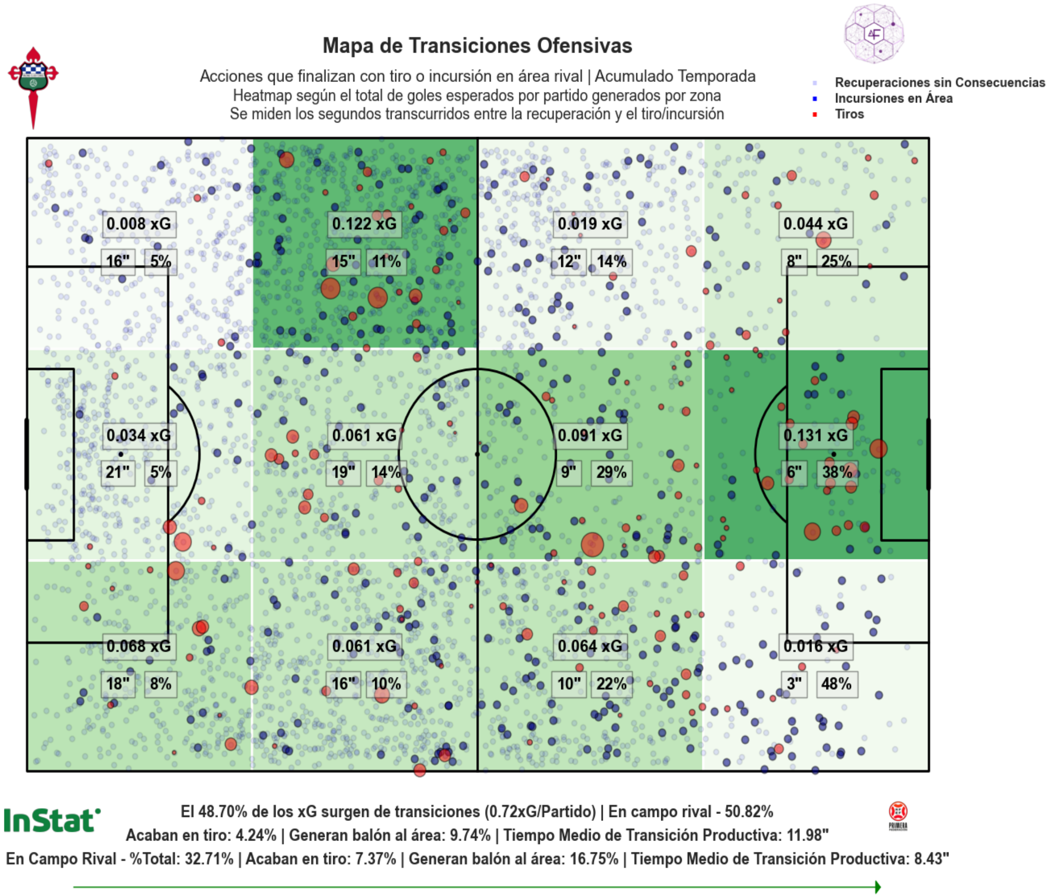
Convex Hulls for Defensive Contribution

Whether conceived at an aggregate level – measuring a set of matches to identify medium/long-term patterns – or studied for a specific game or a portion of it, these visualizations can provide a clear insight into the defensive space occupation of each player.

To create them, all defensive actions of the player in the studied period are analyzed and represented as scattered points across the field. A convex hull is then drawn around those points that are close to a centroid.

As a result, we obtain a representative area focusing on the player's defensive effort location, with a perimeter determined by the dispersion – the area they have the ability to cover or to which they can provide support. In terms of the team, this helps identify not only the defensive structure of the team in question but also specific behaviors, such as the distribution of roles in a double pivot or the assignment of support from wingers or midfielders to full-backs.

Performance Analysis | *Transitions*



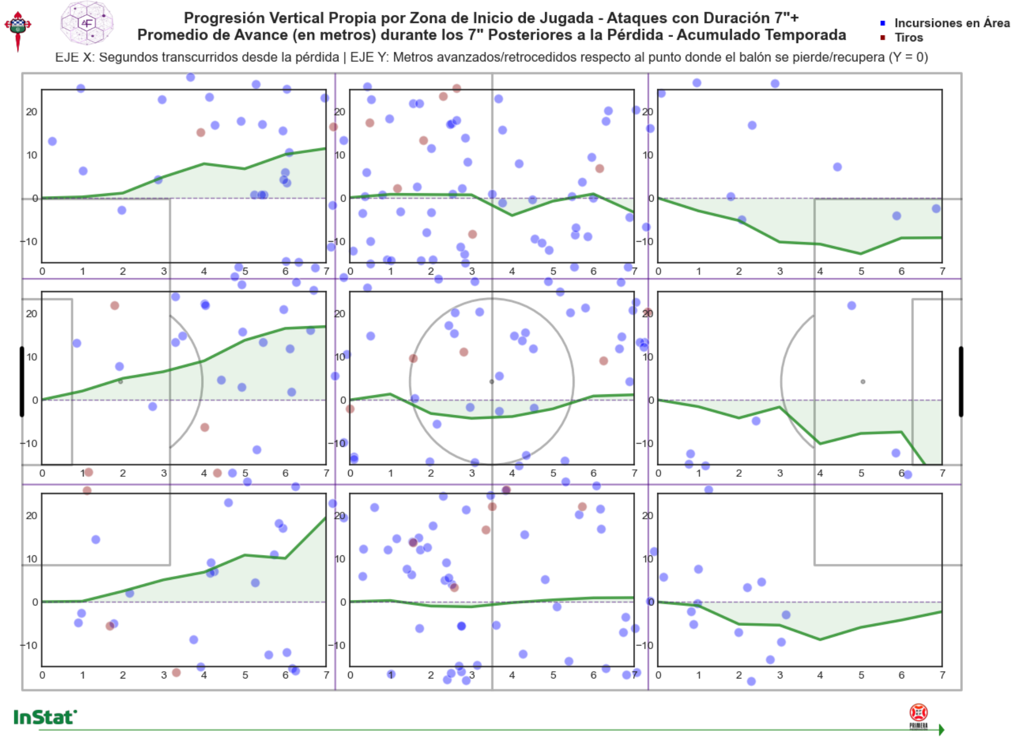
Transitions Matrix, per Recovery Zone

This visualization regards the team's ability to create goal-scoring opportunities through transitions. Specifically, it measures the quality of the chances generated in this aspect of the game, observing the origin or starting point. Areas where recoveries have been more significant are colored more intensely. Likewise, a larger red circle indicates higher-quality chances (xG). Additionally, we can see, by zone, the average time in seconds until a chance is created and the percentage of times a recovery leads to a goal-scoring opportunity.

Studying the evolution of this metric over the course of the season allows us to extract valuable aggregated indicators (see the caption) for the tactical exploitation and preparation of this phase of the game.

We refer to a productive offensive transition as any attack that creates a goal-scoring opportunity – entering the box or taking a shot – within 30 seconds after a recovery.

Performance Analysis | *Transitions*

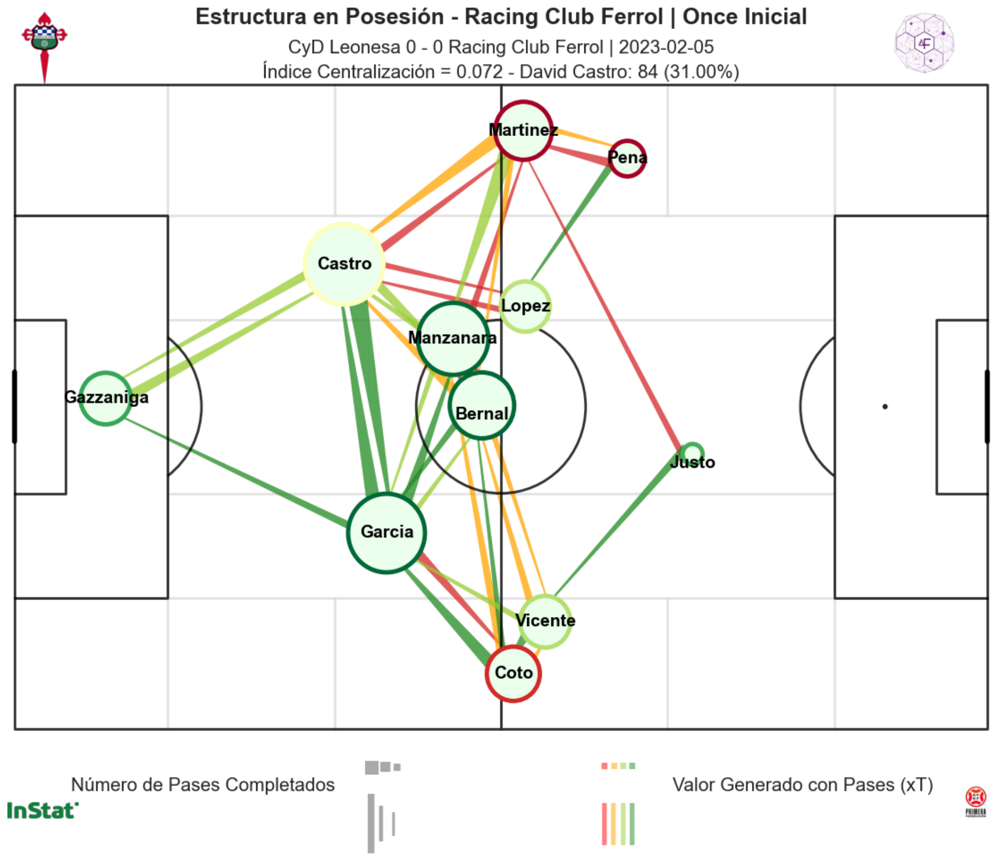


Inmediate Ball Progression in Transitions

A key factor regarding transition play is the ability to progress with the ball vertically in the immediate period following ball recovery. This visualization shows the distance in meters that the team is able to progress in the first seven seconds after winning possession, organized by the field zone where the transition begins.

Its composition allows for identifying how a team approaches transitions, detecting the areas where they initiate transitions more aggressively and where they encounter more resistance. It also reveals whether the team tends to take a more patient approach, consolidating players before launching, or if they are teams that do not seek to create danger in this phase of the game.

Performance Analysis | *Buildup*

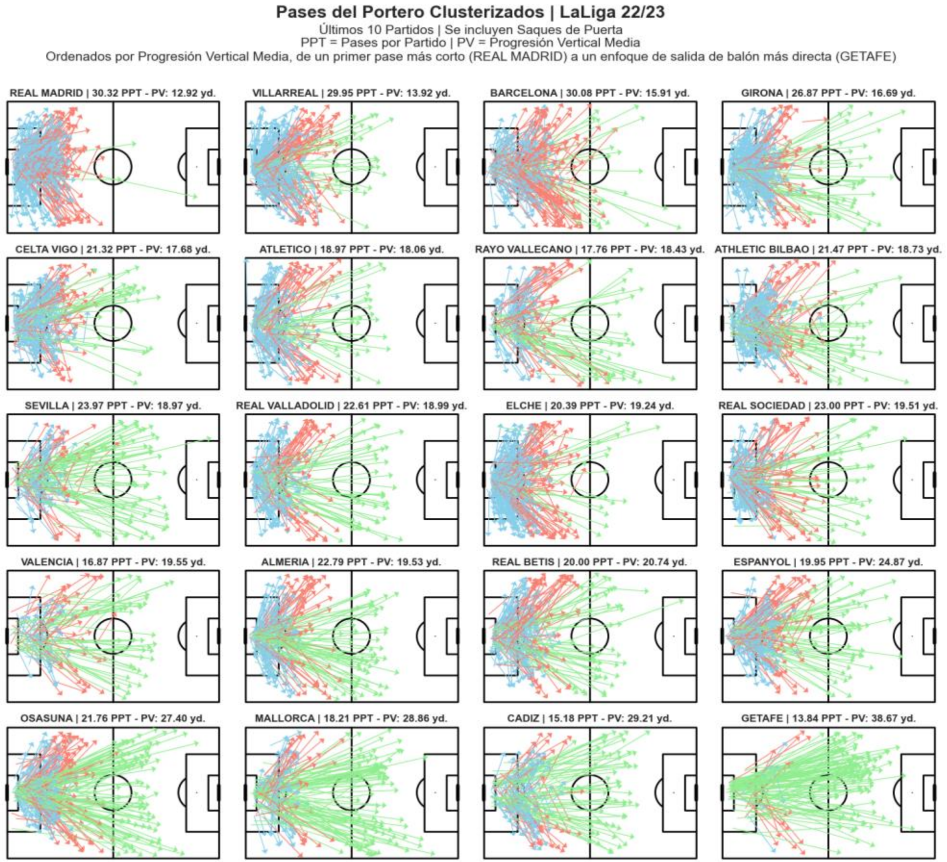


Passing Networks

This diagram aims to represent the team's structure with the ball in a specific match, along with the relationships between participants in positional play. The size of each circle corresponds to the level of participation – passes received – while the color – from red to green – indicates the value – xT – contributed with their passes. For the connections, a similar system is used, with wider lines representing more common connections and green lines indicating connections that, on an aggregated level, bring the team closer – or do so more frequently – to goal-scoring situations.

Additionally, the subtitle reflects the centralization index, which measures the degree of dispersion/concentration of possessions among team members, allowing identification of the player who takes on more organizational responsibilities within the structure.

Performance Analysis | *Buildup*



opta

LaLiga Santander

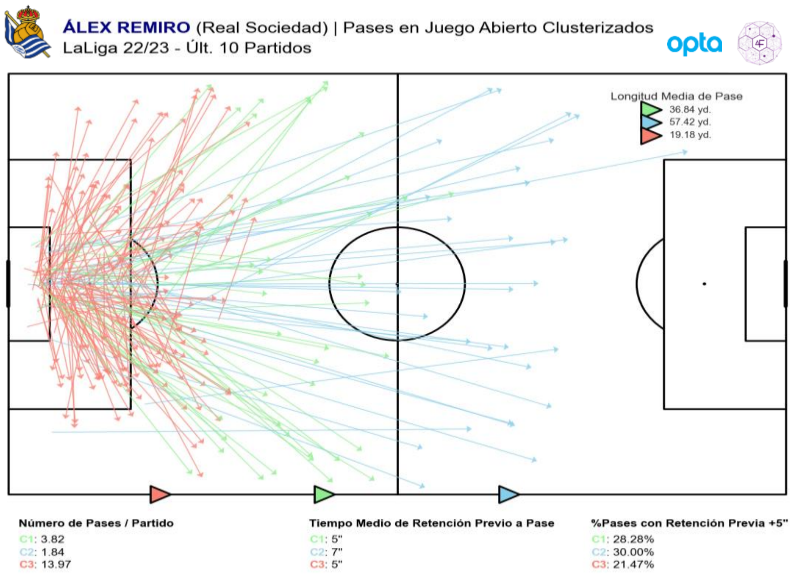
Pass Clustering

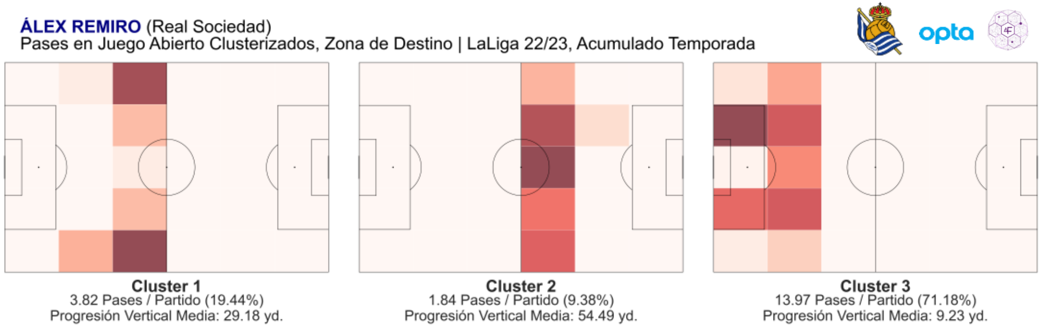
Clustering algorithms allow for the segmentation of a large amount of events that, individually, may not appear related, providing them with a categorization that facilitates analysis.

In this case, all passes made by goalkeepers – including goal kicks – for all LaLiga teams in the final rounds of the 22/23 season are represented. The process helps identify clear patterns in each team's ball distribution, and through direct comparison in the same diagram, we can distinguish different approaches to ball distribution. This ranges from a clear preference for playing to defenders, at the top of the visualization, to a distinct preference for long passes, aiming to progress quickly and create a clear situation through the second play – observed in teams at the bottom of the diagram.

Based on pass length, type, or progression direction, passes are grouped into three categories, visually differentiated to facilitate comparative analyses.

Performance Analysis | *Buildup*





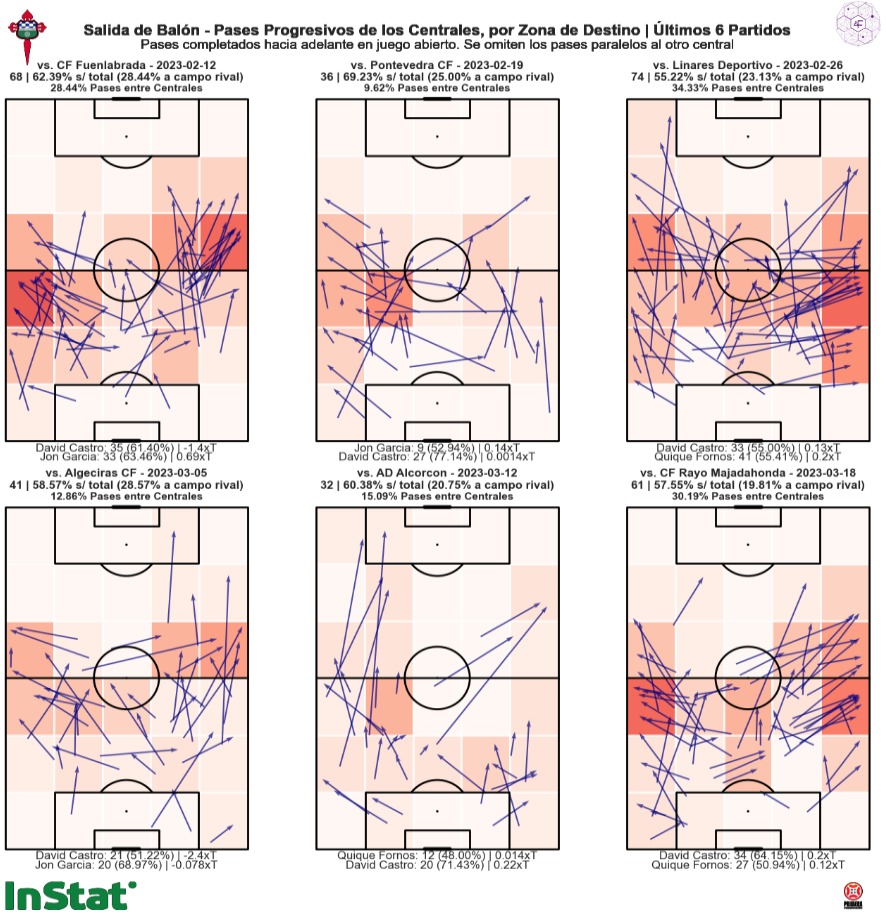
Pass Clustering on Player Events

Once again, we illustrate the clustering model to provide a detailed view of a second interpretation, this time at the player level. The model returns, for a specific player – in this case, a goalkeeper – the passes made during a segmented period of open play.

Furthermore, this segmentation allows us to obtain associated indicators, such as the frequency with which the goalkeeper holds the ball for an extended period, attracting pressure before making a pass – categorized by the resulting pass type – the average length of the pass, or the typical height on the field to which the ball is sent.

In the lower visualization, we observe the typical distribution, by field zone, to which passes are made, categorized by the detected pass type.

Performance Analysis | *Buildup*

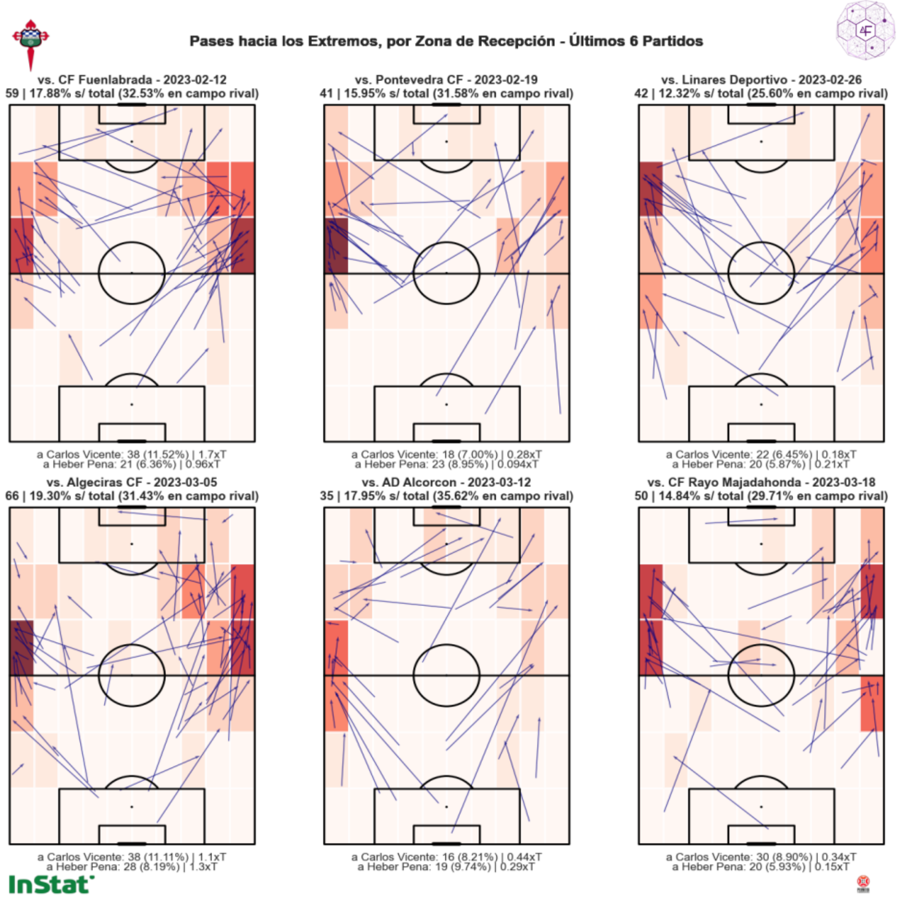


Open-Play Sequences in Buildup from the back

It is worth studying the role, in the context of ball progression, of the interaction between center-backs and other inside players – such as central midfielders, attacking midfielders, and forwards. Through the figure presented below, we observe the distribution of progressive passes directed to players in specified positions – contextualizing these metrics in relation to the total number of progressive passes made by the center-backs. This helps analyze how a team can bypass the opponent's first defensive line.

It is interesting, of course, to analyze where these passes are received, which can be observed by the intensity of the colored zones. Additionally, at the final end of the arrow depicting the pass trajectory, we can identify the receiver with their jersey number. As several aggregated indicators are also calculated, we can easily gauge the significance of these types of passes, understand their value, and determine the volume they represent in comparison to the total passes made by the center-backs.

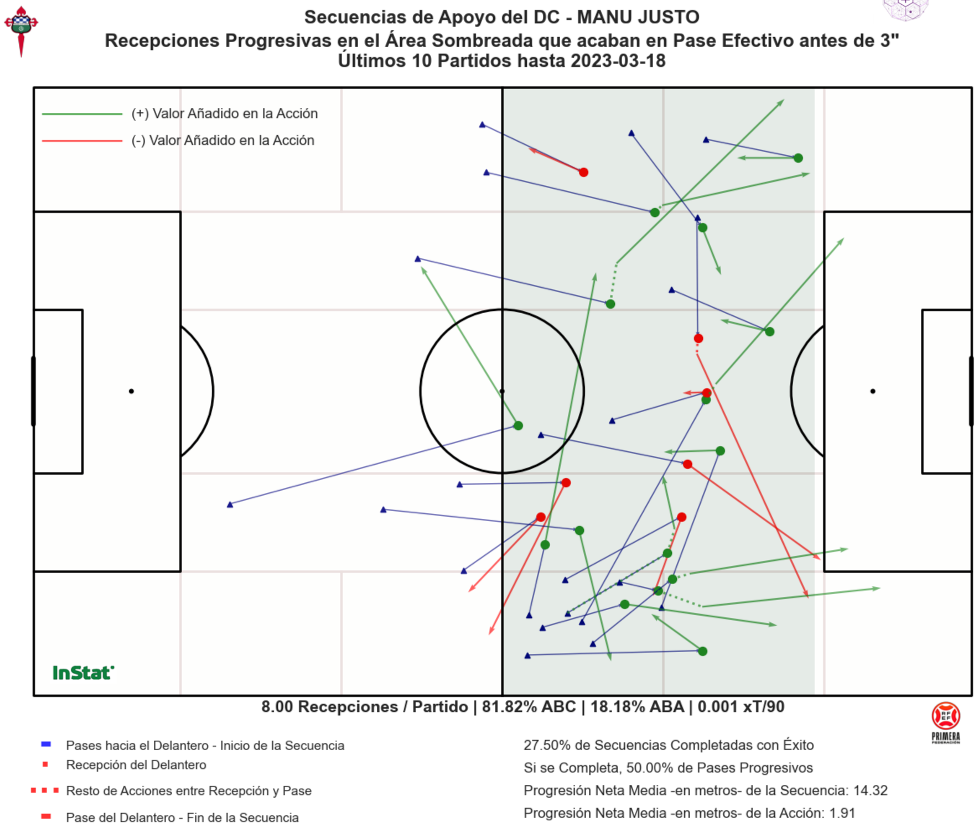
Performance Analysis | *Buildup*



Ball Progression Sequences

For each match, it compiles the set of deliveries received by the wingers, visualizing the total trajectory and the distribution of zones where they occur. This is conceived to understand the typical area where the team is able to force one-on-one situations on the wing. If these situations occur relatively close to the center line of the field, we might conclude that the team lacks the ability to force such situations or create goal-scoring opportunities from the wing. However, if, as is more common, we observe that the receptions occur at a considerable distance, we could establish that the team collectively has the ability to generate advantageous situations for the wingers to create imbalances.

Performance Analysis | *Buildup*

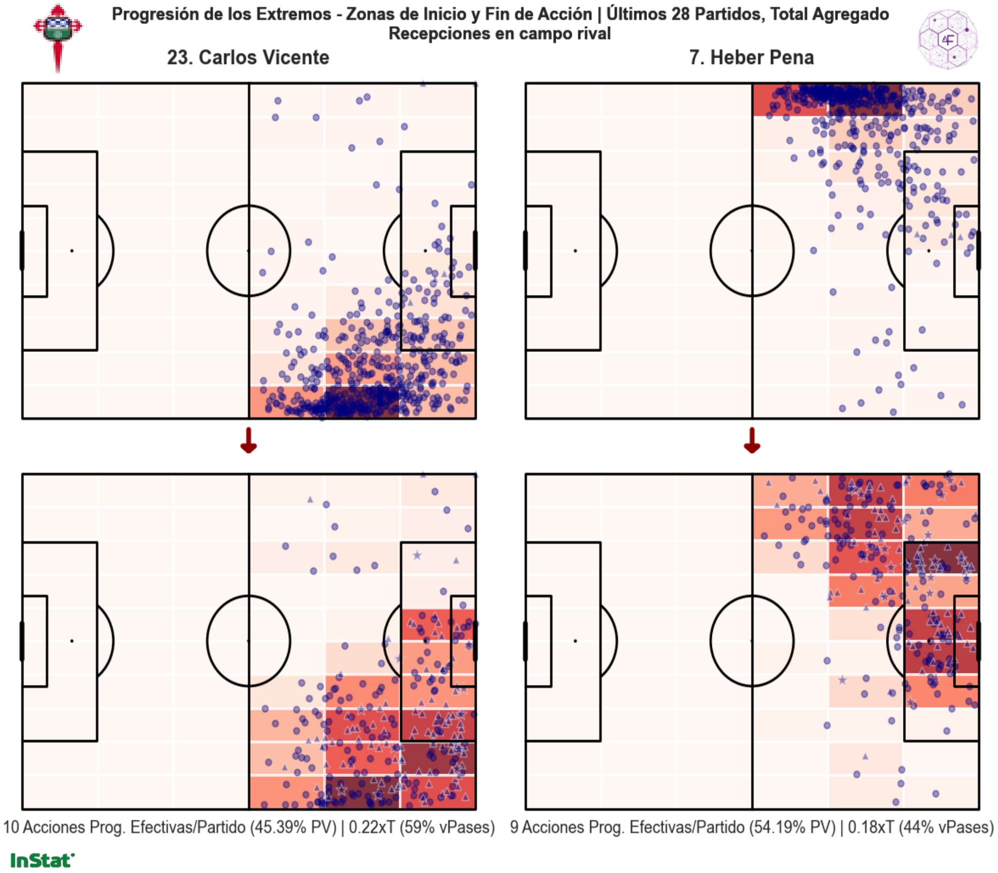


Supporting Sequences

This diagram illustrates the progressive supports – after a forward pass – made by the center forward between the halfway line and the opponent's penalty area. These are supports, not just receptions, as they result from progressive passes, and the ball remains at the feet of the center forward for less than three seconds. This analysis sheds light on the role of the most advanced player in the build-up play and their involvement in the generation of attacking sequences in positional play, measuring whether the player's intervention adds value to the possession based on the xT indicator.

Additionally, key indicators are obtained that define how the sequence unfolds, such as the typical pattern – whether it is a passing one-two (ABA) or an eventual pass to a third player (ABC), depending on how many players are involved – or the progression achieved through this series of passes.

Performance Analysis | *Buildup*

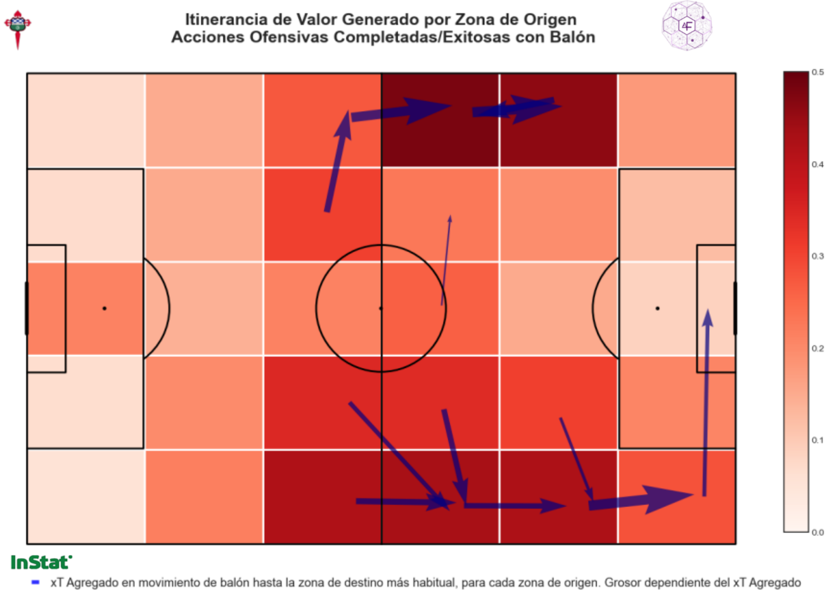


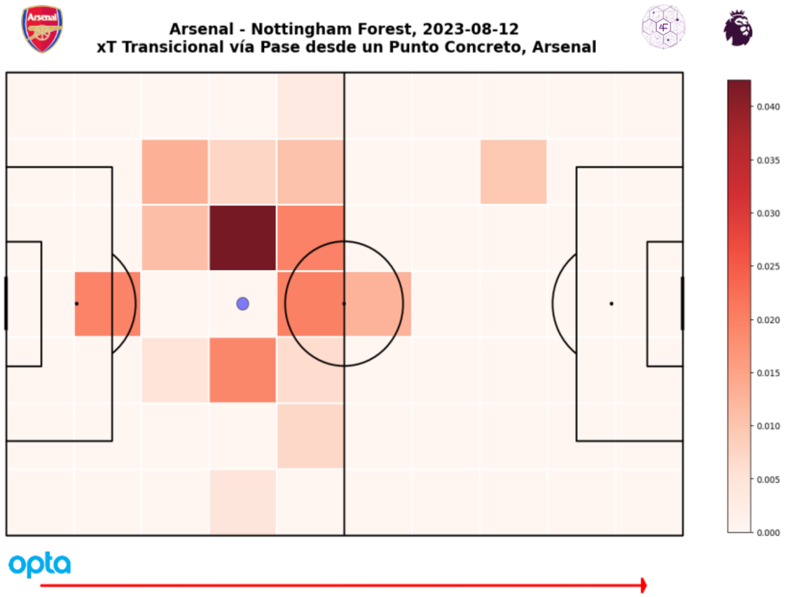
Individual Progression Sequences

This visualization is conceived as an illustrative way to showcase the individual imbalance of offensive players, in this case, the wingers. At the top, the usual reception zones for each player are presented for the cumulative season. Below, the zones of progression completion are arranged, capturing both dribbles and passes and crosses.

We observe that, at a zone level, the flow of actions is slightly different, despite very similar starting points, as both players tend to receive clearly in open positions. While Carlos Vicente progresses more vertically, seeking the end line – whether open or closer to the small area – it is evident that Heber Pena has a higher percentage of his actions in interior zones, both outside and inside the penalty area.

Performance Analysis | *Buildup*

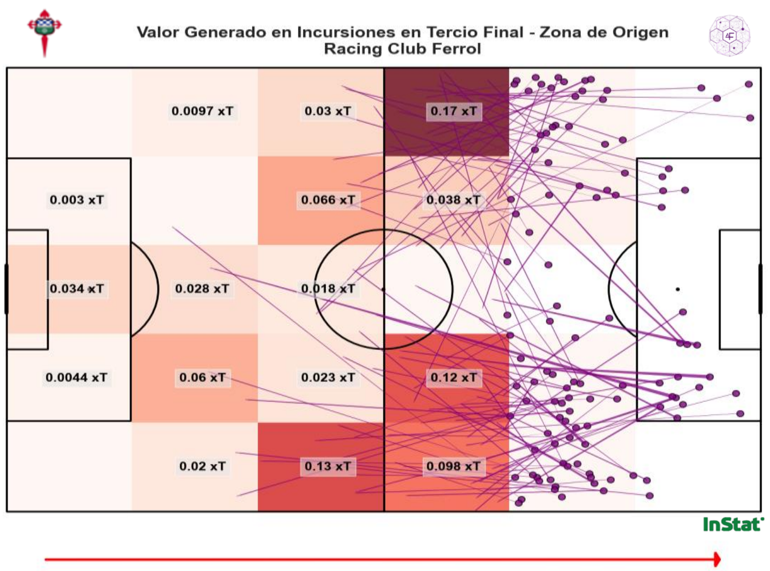


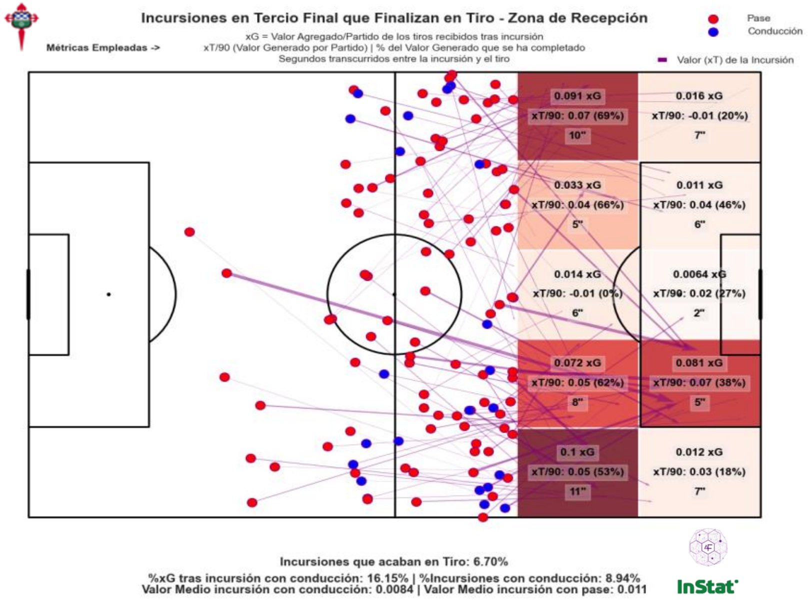


Transitional Value Flows Generated in Buildup

These diagrams illustrate how the analyzed team tends to create high-value situations – those that bring the team closer to forcing high-quality goal-scoring opportunities (high xG). Using the Expected Threat indicator calculation model, the transitional matrix distributes the value created per zone, and through the arrows, it shows the zone toward the danger is typically generated.

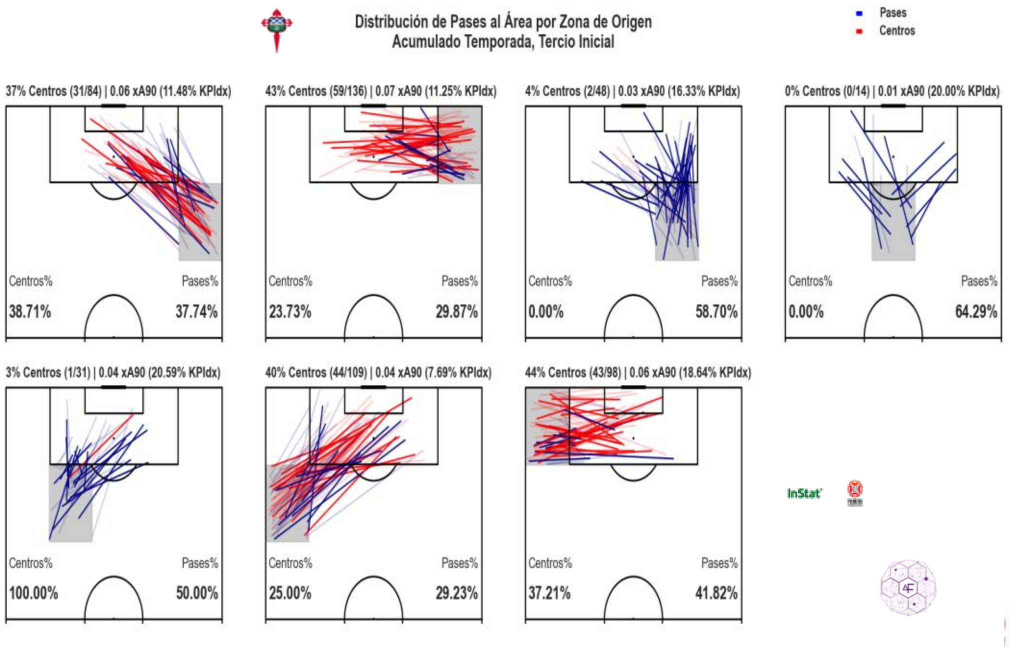
Performance Analysis | *Chances Creation*





Incursions into Final Third

This visualization presents, by origin zone, the aggregated distribution of the value generated in possession – xT – with passes to the final third of the field, over the course of a season. This allows us to understand from which zones more dangerous passes are generated. The map on the right-hand side distributes, based on expected goals (xG), the reception points of transitions from which the team has the ability to generate the most danger. Additionally, the average time elapsed, in seconds, between the penetration and the shot is included.



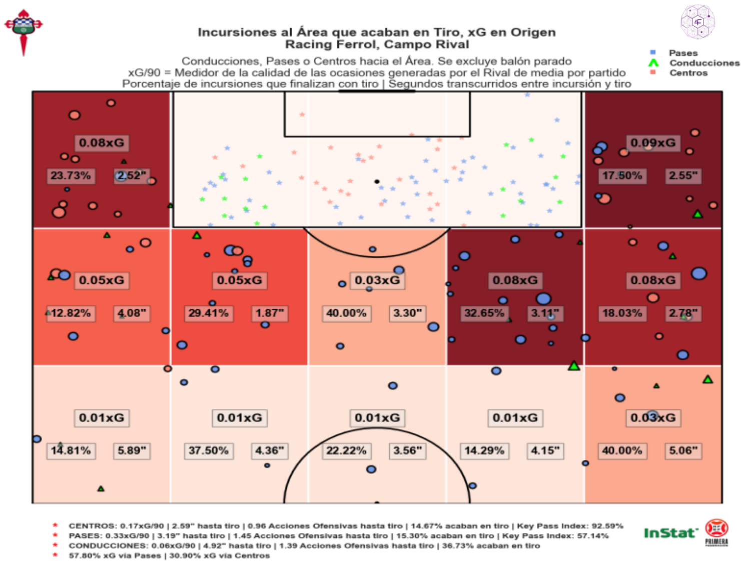
Incursions into Penalty Box

This visualization provides information about the origin and dominant type of delivery, by origin zone, of the team in question when entering the penalty area and creating goal-scoring opportunities. Each added campogram represents an area adjacent to the penalty area, distinguishing between crosses – in red – and passes – in blue.

Added as explanatory data for the volume are the accuracy percentages – by type of delivery – and the percentage of crosses compared to the total deliveries. To understand the quality of the danger generated by zone, we use the expected assists (xA) data by zone and the Key Pass Index (KPIdx), an indicator that measures the percentage of occasions when a delivery precedes an immediate shot by a shooter.

In the specific case illustrated, we observe that Racing de Ferrol (2022/23) does not concentrate its threat in any particular area, although it has the ability to generate much more danger when gaining the end line from outer areas, with the depth of its two wingers: Carlos Vicente and Héber Pena. From these zones (2nd and 5th campogram), the Galician team generates 0.13xG per match solely through shots that follow an immediate attempt.

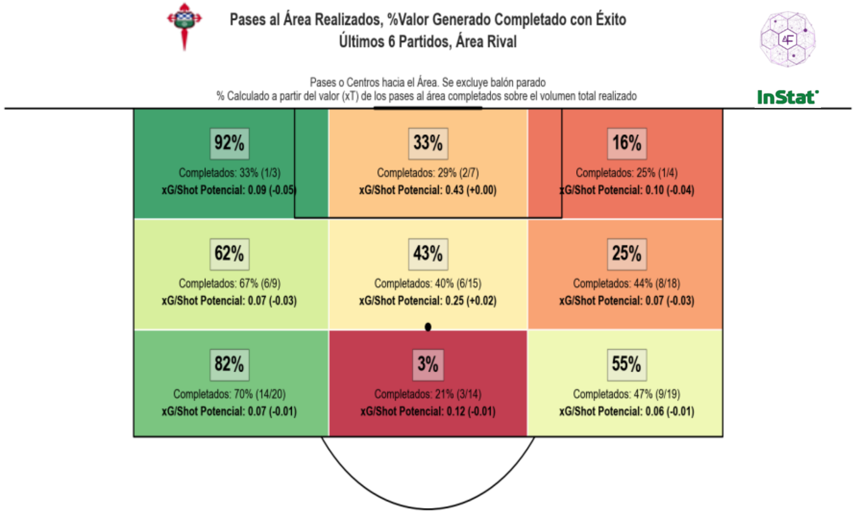
Performance Analysis | *Chances Creation*



Threat Generated through Box Incursions, per Start Zone

This visualization demonstrates the team's ability to threaten with penetrations. By origin zone, within a division of areas in the opponent's field – excluding the penalty area – the level of danger from penetrations from these areas is measured, whether through passes, crosses, or dribbles. It shows, for each of these zones, the xG per game associated with these goal-scoring opportunities, the success rate in penetrations, and the average seconds elapsed between entering the penalty area and taking a shot.

Below the illustration, aggregated metrics for the season can be observed, providing insights into the team's quality and effectiveness in the mentioned three specialties.



Threat Generated through Box Incursions, per End Zone

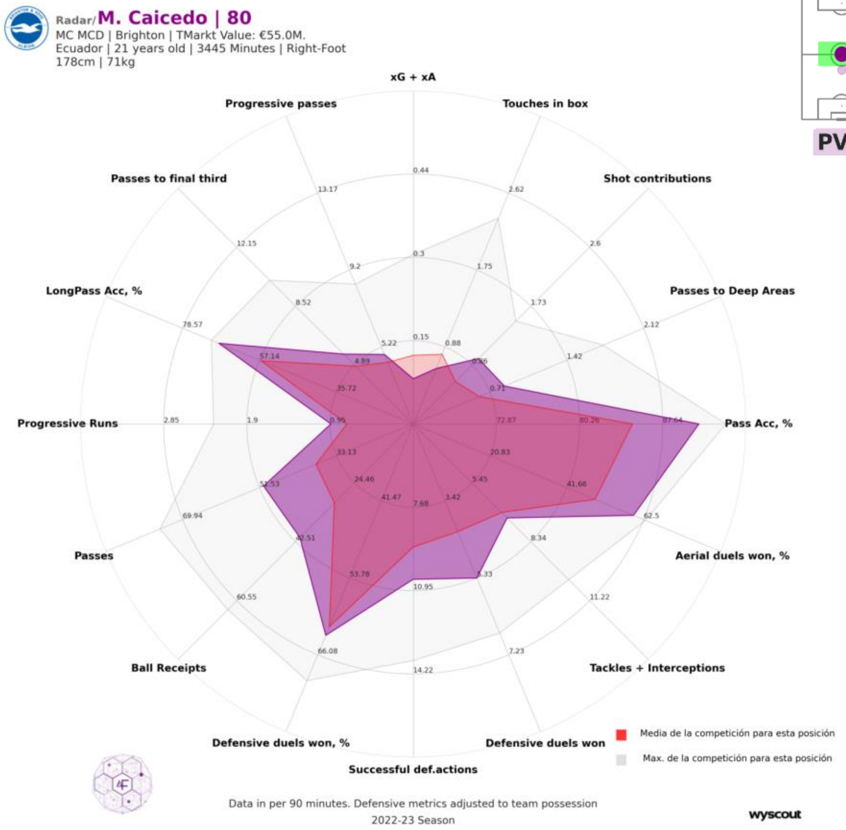
This visualization serves as a complement to the one shown on the left, as it helps verify, by the zone of penetration reception, the degree of effectiveness (success rate), the volume of value generated (%xT completed – bold value) in the penetration that continues within the penalty area – meaning it has not been repelled by the opposing defense – and the level of threat that these deliveries pose – xG/Shot Potencial (average expected goals associated with a shot if it were to occur at the moment and place of receiving the pass into the area).

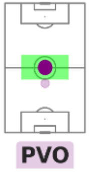
A high completed value, and therefore marked in green in the destination zone, implies high profitability (risk of the pass vs. reward/success) and, consequently, a warning sign for future opponents regarding defensive vigilance in that area.

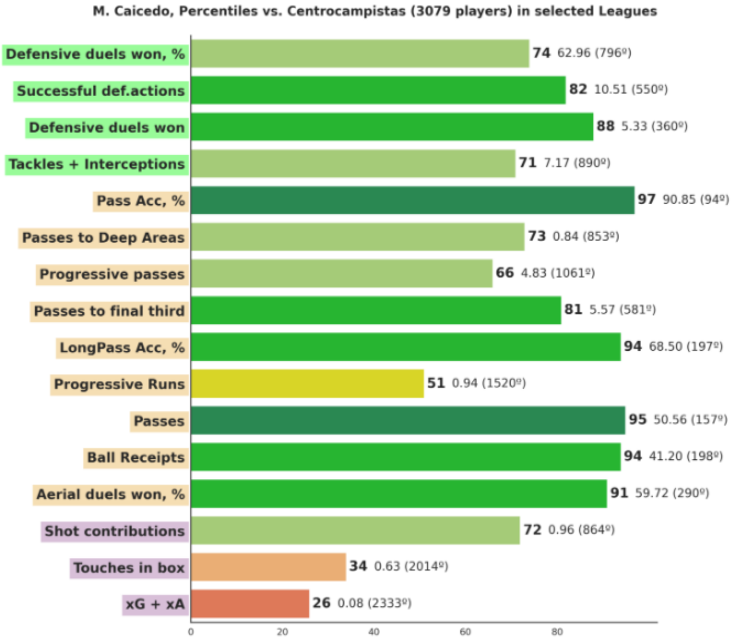
Recruitment Analysis | *Player Reports*

Link to Interactive Dashboard

Streamlit



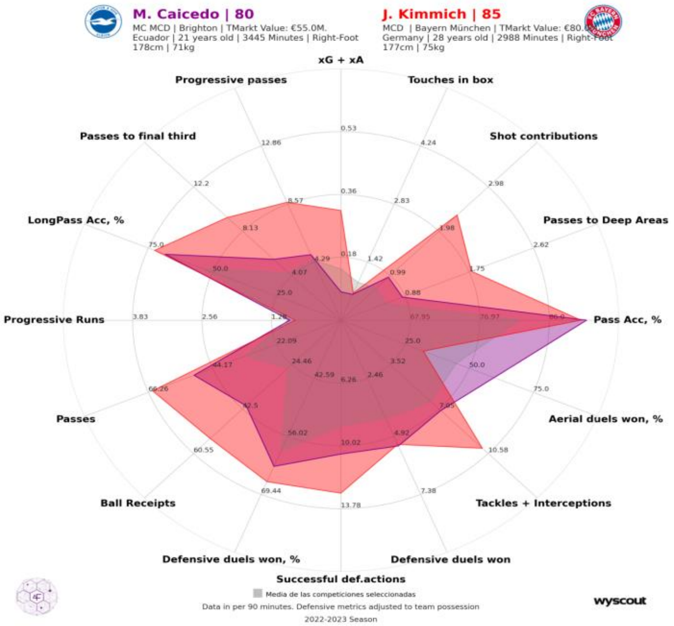


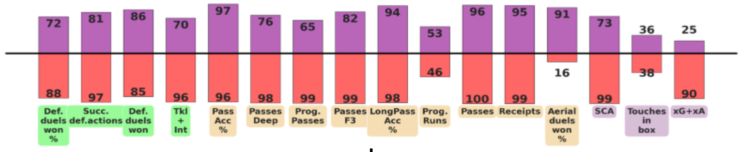


Defensa	Buildup	Ataque
76	86	30

* Data from 2022/23 Season

Recruitment Analysis | *Player Reports*





76 **86** **30**

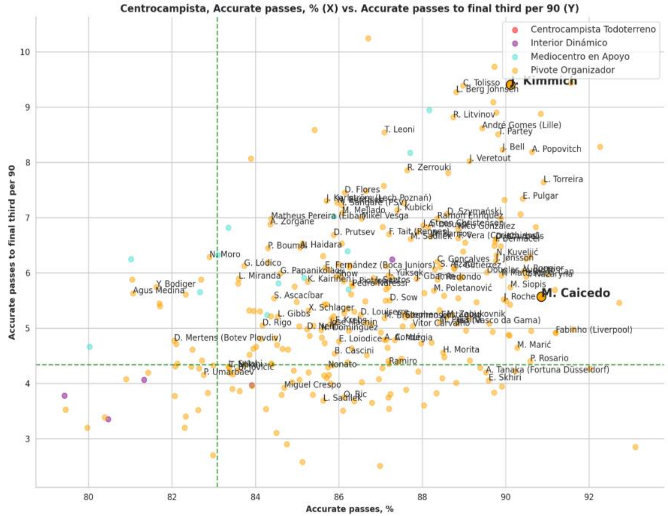
M. Caicedo | 80

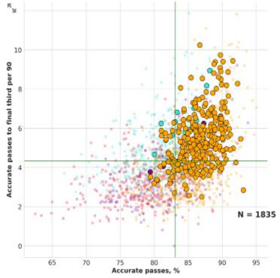
92 **77** **63**

J. Kimmich | 85

M. Caicedo vs. Comparación + Centrocampista de Bayern München

Player	Posición	Equipo	Cluster	Similarity	Performance
M. Caicedo	MC, MCD	Brighton	Pivote Organizador	100	80
R. Gravenberch	MCD, MCC	Bayern München	Pivote Organizador	87.74	87
J. Kimmich	MCD	Bayern München	Pivote Organizador	77.01	85
L. Goretzka	MCD	Bayern München	Pivote Organizador	71.76	89
L. Sané	ED, MC	Bayern München	Interior Dinámico	48.96	81





Selected Players (Top300 Similarity)
Resto

Cluster	Total	Selected	%
Centrocampista Todoterreno	219	0	0
Interior Dinámico	403	5	1.24
Mediocentro en Apoyo	370	13	3.51
Pivote Organizador	843	283	33.57

Link to Interactive Dashboard → Streamlit

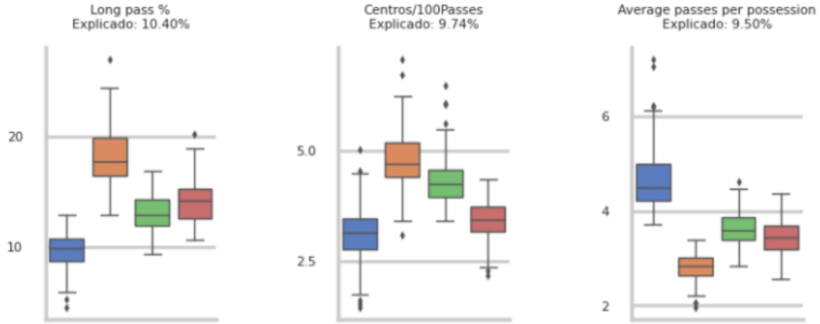
* Data from 2022/23 Season

Recruitment Analysis | *Teams Segmentation*

Assigning Playing Styles per Squad and Game Phase

This procedure aims to group a set of analyzed teams for each phase of the game into various clusters based on a series of descriptive variables.

In this example, we observe the result of a clustering process in the positional construction phase, using various metrics – on the right, we can see the differences between the groups in three of them – resulting in four groups. Below, we can learn about the characteristics of these four groups in possession phase. Additionally, we show which teams belong to each of the resulting clusters.



* Data from 2022/23 Season

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Equipo	Competicion	xG_DIF
Brann	NOR_Eliteserien	2.18
Benfica	POR_PrimeiraLiga	1.69
Celtic	SCO_Premiership	1.69
Crvena Zvezda	SRB_Superliga	1.69
Rangers	SCO_Premiership	1.62
Ajax	NED_Eredivisie	1.58

Equipo	Competicion	xG_DIF
Sturm Graz	AUT_Bundesliga	1.01
Instituto	ARG_LigaProfesiona	0.49
Sigma Olomouc	CZE_FortunaLiga	0.41
CFR Cluj	ROM_Superliga	0.37
Luton Town	ENG_Championshi	0.35
Cercle Brugge	BEL_FirstA	0.27

Equipo	Competicion	xG_DIF
Slavia Praha	CZE_FortunaLiga	1.27
Elfsborg	SWE_Allsvenskan	1.12
Sparta Praha	CZE_FortunaLiga	1.1
Levski Sofia	BUL_FirstLeague	1.04
Salzburg	AUT_Bundesliga	0.99
SJK	FIN_Veikka	0.96

Equipo	Competicion	xG_DIF
Botafogo	BRA_Brasileirao	0.97
CSKA Sofia	BUL_FirstLeague	0.88
Estudiantes	ARG_LigaProfesiona	0.51
Caen	FRA_Ligue2	0.46
Talleres Córdoba	ARG_LigaProfesiona	0.43
Koper	SVN_PrvaLiga	0.34

Buildup

- C1: más combinaciones por cada posesión. Más ataques posicionales y más largos. Mayor dificultad para jugar entre líneas. Menos juego por banda y poco pase largo. Más facilidad para asentarse con balón. Entradas a tercio final con pases cortos. Ritmo de partido más alto. Capacidad para llegar en posesión a zonas profundas del campo. Salidas rápidas tras recuperar y contrapresión tras pérdida. Talento para entrar al área con conducciones.
- C2: menos pases por posesión, juego más directo y simplificado. Más juego por banda y más centros al área. Entradas a tercio final con pases largos. Centros como modo de encontrar la profundidad y tiros obtenidos con menos pases. Pocas situaciones de uno para uno en zonas avanzadas. Poco propenso a buscar contragolpes.
- C3: Juego algo más directo, combinaciones rápidas y posesiones cortas. Más juego por banda en tres cuartos de campo, con centros y conducciones como modo de encontrar la profundidad. Entradas a tercio final con pases cortos. Salidas rápidas tras recuperar y contrapresión tras pérdida. Más propenso a buscar contragolpes.
- C4: más pases en los ataques posicionales. Menor recurso a la individualidad y al juego directo en tres cuartos. Menos juego por bandas pero mayor tendencia al pase largo. Más dificultad para asentarse con balón. Ritmo de partido más bajo. Menos talento para encontrar profundidad con pases o conducciones y a llegar a zonas claras de tiro. Poco propenso a buscar contragolpes.

Link to Interactive Dashboard

Streamlit

Recruitment Analysis | *Players Segmentation*

Assigning Playing Roles per Position

This procedure aims to group a set of analyzed players for a specific position into various clusters.

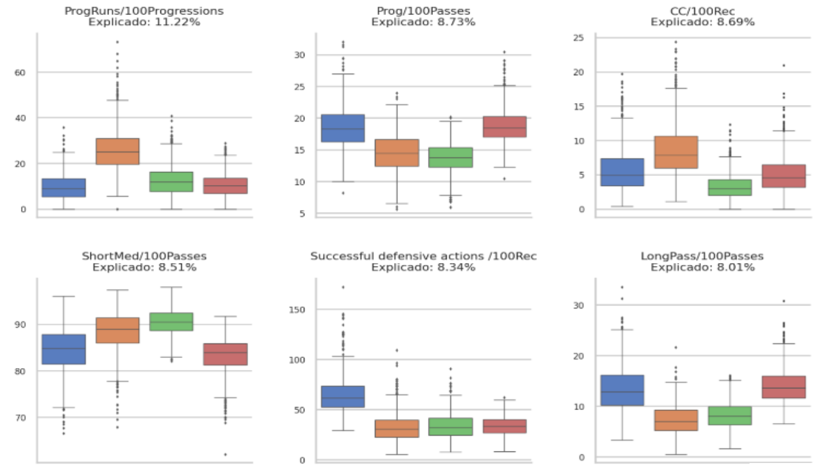
In this example, we observe the result of a clustering process carried out on central midfielders – wingers and attacking midfielders are excluded unless they have played enough minutes as pivots or central midfielders – using various metrics considered descriptive of these positions. On the right, we can see the differences between the resulting groups in several of these metrics, resulting in four types of roles. Below, we can learn about their characteristics and differences. Additionally, we show which players belong to each of the resulting clusters.

Player	Equipo	Posición	Birth country
J. Akpa Akpro	Empoli	MC	France
W. McKennie (Leeds U	Leeds United	MCD	United States
G. Escalante	Cádiz	MC	Argentina
Pablo Ibáñez	Osasuna	MC	Spain
C. Nørgaard	Brentford	MCD	Denmark
T. Krauß	Schalke 04	MCD	Germany
T. Souček	West Ham United	MCD	Czech Republic
J. Stage	Werder Bremen	MC	Denmark

Player	Equipo	Posición	Birth country
F. de Jong	Barcelona	MC	Netherlands
F. Valverde	Real Madrid	MC	Uruguay
S. Diop	Nice	EI	France
N. Boujellab	Schalke 04	MC	Germany
R. Loftus-Cheek	Chelsea	ED	England
Bernardo Silva (Manch	Manchester City	ED	Portugal
K. Thuram	Nice	MC	France
G. Lo Celso	Villarreal	EI	Argentina

Player	Equipo	Posición	Birth country
Rodri (Manchester	Manchester City	MCD	Spain
L. Goretzka	Bayern München	MCD	Germany
E. Camavinga	Real Madrid	LI	France
R. Gravenberch	Bayern München	MCD	Netherlands
Renato Sanches	PSG	MC	Portugal
Fabián Ruiz	PSG	MC	Spain
J. Kimmich	Bayern München	MCD	Germany
V. Rongier	Olympique Marseille	MC	France

Player	Equipo	Posición	Birth country
H. Sakhi	Auxerre	MC	Morocco
B. van den Boomen	Toulouse	MCD	Netherlands
T. Koopmeiners	Atalanta	MC	Netherlands
R. Mandragora	Fiorentina	MCD	Italy
Rúben Neves (Wolverh	Wolverhampton Wanc	MCD	Portugal
R. de Paul	Atlético Madrid	MC	Argentina
S. Tonali	Milan	MCD	Italy
P. Lees-Melou	Brest	MCD	France



*Data from 2022/2023 Season

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Centrocampista

- C1 - CENTROCAMPISTA TODOTERRENO (CTT): más pases largos, más acciones defensivas y menos participación con balón, más estáticos con balón, más pases a tercio final, menos pases clave. Especialistas defensivos (pivotes o interiores).
- C2 - INTERIOR DINÁMICO (IND): menos pases largos, más progresión con balón, más generación de oportunidades, más pases cortos, menos progresiones por recepción, más llegada al área, más pases clave. Interiores dinámicos -creativos, móviles y/o llegadores-.
- C3 - PIVOTE ORGANIZADOR (PVO): menos pases largos, menos participación en tres cuartos de campo y más participación con balón, más pases cortos, menos progresiones por recepción, menos envíos a tercio final, menos pases clave y más intensidad defensiva. Pivotes organizadores e interiores de mucha posesión y poco juego entre líneas.
- C4 - MEDIOCENTRO EN APOYO (MEC): más pases largos, más progresiones con pase, menos llegada al área, más pases a tercio final de campo, más estáticos con balón. Acompañantes del pivote o interiores de base. Capacidad de asociación notable, pero menor responsabilidad organizativa que el pivote organizador

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Recruitment Analysis | *Similarity Algorithms*

VINICIUS JÚNIOR
Jugadores Similares <30 Años | Sólo Primeras Divisiones

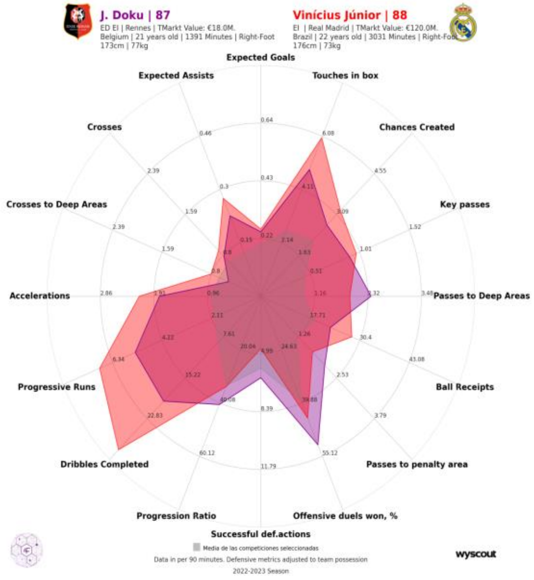
wyscout

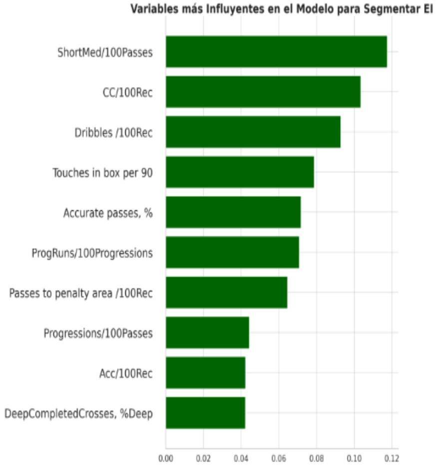
Jugador	Posición	Edad	Equipo	País	Similitud	Rol
J. Doku	ED, EI	21	Rennes	Belgium	85.97	Extremo Autosuficiente
M. Daramy	EI	21	København	Denmark	84.67	Extremo Profundo
K. Mitoma	EI	26	Brighton	Japan	82.57	Extremo Autosuficiente
R. Mirzov	EI, DC	29	Khimki	Russia	82.55	Extremo Autosuficiente
Galeno	EI	25	Porto	Brazil	82.1	Extremo Autosuficiente
D. Kutesa	MCO, EI	25	Servette	Switzerland	82.04	Extremo Autosuficiente
T. Keskinen	EI, ED	20	HJK	Finland	81.99	Extremo Profundo
K. Kvaratskhelia	EI	22	Napoli	Georgia	81.26	Extremo Autosuficiente
O. Dembélé	ED, EI	26	Barcelona	France	80.4	Extremo Autosuficiente
Rafael Camacho	EI, DC	22	Aris	Portugal	80.07	Extremo Autosuficiente
Bruma	EI	28	Sbraga	Guinea-Bissau	79.56	Extremo Autosuficiente
V. Misidjan	EI	29	Twente	Netherlands	79.56	Extremo Profundo
O. Sahraoui	EI	22	Heerenveen	Norway	79.32	Extremo Autosuficiente
Gabriel Martinelli	EI	21	Arsenal	Brazil	79.24	Extremo Autosuficiente
Éverton	EI	27	Flamengo	Brazil	78.55	Extremo Autosuficiente

***Data from 2022/2023 Season**

This model relies exclusively on similarities between players, calculating based on indicators (see table below) that are more explanatory for the specific position. It will be useful in cases where a team decides to replace a player by looking for a copy that closely resembles them.

In this case, we observe that the model prioritizes, when looking for players similar to Vinicius Jr, wingers who seek one-on-one situations from very wide areas and are fast, with great dribbling skills. Below, we see in detail the comparison between Jeremy Doku and the Brazilian, along with the variables that have the greatest influence when segmenting wingers within the model.





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Recruitment Analysis | *Recommendation Systems*

MANCHESTER CITY
Top DFC (<30años) más Adecuados al Modelo de Juego para la Posición de DFC
Sólo Primeras Divisiones

wyscout

Jugador		Equipo	Posición	País	Edad	Adecuación	Rol
D. Popov		Dynamo Kyiv	DFC	Ukraine	24	90.38	Defensa con Toque
A. Kovačević		Ferencváros	DFC	Bosnia and Herzegovina	29	89.31	Defensa con Toque
J. Sands		Rangers	DFC, MCD	United States	22	88.92	Defensa con Toque
J. Gomez		Liverpool	DFC, LD	England	26	88.7	Defensa con Toque
P. Chatzidiakos		AZ	DFC, LD	Greece	26	87.94	Defensa con Toque
B. Kalaica		Lokomotiva Zagreb	DFC	Croatia	25	87.58	Defensa con Toque
V. Yermakov		Chornomorets	DFC, LI	Ukraine	30	87.25	Defensa con Toque
Éder Militão		Real Madrid	DFC	Brazil	25	86.97	Defensa con Toque
V. Screciu		Uni Craiova	DFC, MCD	Romania	23	86.91	Defensa con Toque
D. Zec		Celje	DFC	Slovenia	23	86.79	Defensa con Toque
E. Tapsoba		Bayer Leverkusen	DFC	Burkina Faso	24	86.5	Defensa con Toque
F. Dagerstål		Lech Poznań	DFC	Sweden	26	86.07	Defensa con Toque
V. Baboglo		Oleksandria	DFC	Ukraine	24	86.0	Defensa con Toque
M. Lacroix		Wolfsburg	DFC	France	23	85.48	Defensa con Toque
A. Rrahmani		Napoli	DFC	Kosovo	29	85.41	Defensa con Toque

***Data from 2022/2023 Season**

The model quantifies and aggregates the playing style of teams to subsequently profile each footballer in a specific position based on the key metrics of each role, with the purpose of identifying a set of players who demonstrate a greater suitability for the desired role in a particular team and tactical context.

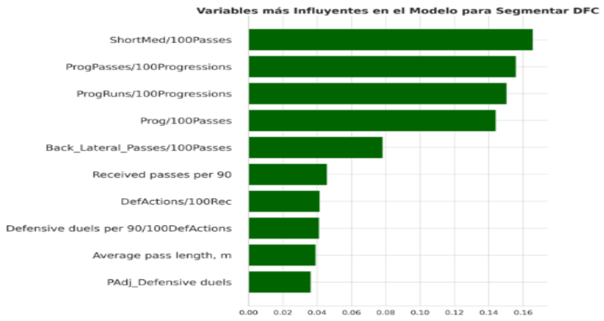
The players given by the model will have more suitable conditions to meet the team's needs when entering the market. Therefore, they will require a shorter adaptation process and will be familiar with similar playing mechanisms.

¿How to calculate it?

Preference for center-backs from teams whose playing style is similar to that of Manchester City:

- Formations with four defenders (mainly 4-3-3).
- Fewer faced positional attacks and more transitions. Aggressiveness after losing possession.
- More combinations per own possession. More positional and longer attacks.

Individually, they should resemble Manchester City's center-backs, regarding these input variables:



Link to Interactive Dashboard

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