



A Computational Exploration of Football Player Performance at the FIFA World Cup 2022 Using StatsBomb Event and 360° Spatial Data

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Received: 17 June 2026, Approved: 20 August 2026, Published: 30 September 2026

Abstract

Study purpose. This study explores the descriptive and structural characteristics of individual player performance at the FIFA World Cup 2022 using rich event and 360° spatial data, with the aim of demonstrating that advanced metrics provide a more discriminative profile of player contribution than conventional box-score statistics.

Materials and methods. Open event data and 360° freeze-frame data for all 64 matches were extracted using the statsbombpy interface and processed through a reproducible Python pipeline adapting the CRISP-DM workflow. Twenty-five advanced per-90-minute metrics were engineered for 681 players, of whom 346 met a minimum-playing-time threshold of 180 minutes. Descriptive statistics, Pearson and Spearman correlations, and K-means clustering were applied.

Results. Expected goals correlated strongly with goals scored ($r = 0.75$), whereas expected assists correlated only weakly with recorded assists ($r = 0.22$), revealing a substantial pool of creative contribution that conventional statistics fail to capture. Position and confederation profiles differed systematically, and unsupervised clustering recovered interpretable playing-style groups that cut across formal positional labels.

Conclusions. Advanced event and spatial metrics expose tactically important, under-recognised contributions and provide a reproducible analytical baseline for subsequent network- and graph-based player evaluation

Keywords: Football Analytics, Expected Goals, Player Performance, Statsbomb, FIFA World Cup 2022, Computational Analysis

DOI: <https://doi.org/10.52188/ijpeess.v6i3.2260>

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Introduction

Modern football has become an increasingly data-rich domain, in which the evaluation of player performance has progressively shifted from simple counting statistics toward

computational analysis of fine-grained event and spatial data. The growing availability of open datasets and tracking technologies has enabled researchers to study not only the visible outcomes of play, such as goals and assists, but also the underlying processes that create and prevent scoring opportunities. Systematic reviews of artificial intelligence in football confirm that the field is rapidly maturing, with computational methods increasingly able to capture tactical behaviour and collective dynamics that traditional statistics overlook (Jia et al., 2025; Teixeira et al., 2025).

Within this landscape, the FIFA World Cup 2022 occupies a special position: it is one of the richest publicly available football datasets, providing event data and 360° freeze-frame snapshots that record the position of every visible player at key moments. Despite this richness, much of the existing analysis of international tournaments still relies on conventional box-score statistics, which are known to provide an incomplete picture of player quality. Running-performance metrics, for example, show only weak associations with player value at the World Cup level, suggesting that physical output alone does not adequately represent meaningful contribution (Kilci et al., 2025). Composite and advanced indicators are increasingly advocated as more faithful summaries of performance (Thrane, 2024).

Beyond its tactical significance, the accurate evaluation of player performance also carries direct economic weight, since it underlies the recruitment and transfer decisions that shape an increasingly large global market. In 2022, the year of the present dataset, men's professional football reached a new high of 20,209 international transfers, involving 4,770 clubs, 17,291 players, and 182 FIFA member associations (FIFA, 2022). This volume continued to grow in subsequent years, reaching 24,558 transfers and a record USD 13.08 billion in transfer-fee spending by 2025 (FIFA, 2025), as shown in Figure 10. While the present study is descriptive and does not address market valuation directly, this growing market underlines the practical stakes of analytical tools that can surface player contributions left understated by conventional statistics.

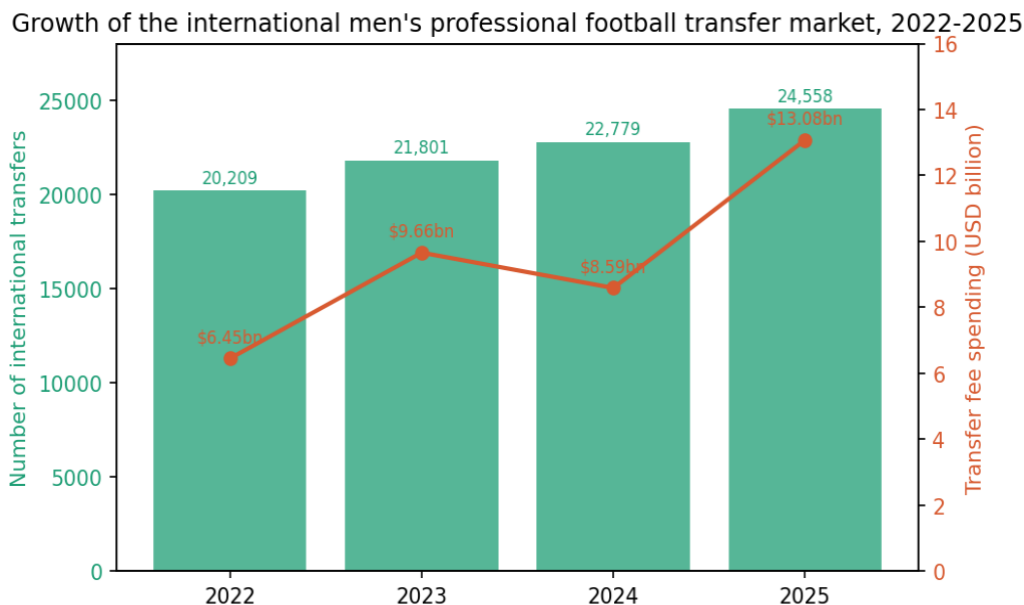


Figure 1. Growth of the international men's professional football transfer market, 2022-2025, based on FIFA Global Transfer Reports

Expected goals (xG) and related metrics have emerged as influential tools for quantifying the quality of attacking actions beyond their immediate outcome (Anzer & Bauer,

2021; Mead et al., 2023). However, xG and its variants remain primarily shot-centric, capturing the quality of finishing opportunities while undervaluing build-up play and off-ball contribution (Corsaro et al., 2025; Narayanan & Pifer, 2023).

This limitation motivates a broader exploration of advanced metrics that describe progression, pressing, and creative involvement, and ultimately points toward network- and graph-based representations of the game (Ievoli et al., 2021; Raabe et al., 2022).

Within the Indonesian scientific literature, football analytics has attracted growing interest, although existing work has generally relied on match-level statistics or manually coded tactical observations rather than rich player-level event and spatial data. Decision-tree methods such as C4.5 have been applied to predict UEFA Champions League winners from club-level attributes such as squad quality, finances, and coaching (Tandian et al., 2019), while ensemble methods including XGBoost and Gradient Boosting have achieved very high classification accuracy in forecasting BRI Liga 1 Indonesia match outcomes from aggregated match statistics such as possession and shot accuracy (Hidayat et al., 2024). At the tactical level, association-rule methods such as FP-Growth have been used to mine ball-distribution patterns of the Indonesian national team from manually annotated match video (Ardiantoro et al., 2023). Complementing this performance-oriented literature, sentiment-analysis studies have examined how Indonesian social media users respond to the national team's results and policies (Nugraha & Zakiyah, 2025), reflecting a broader appetite for data-driven engagement with the sport. However, none of these studies has made use of high-resolution, player-level event and 360° spatial data of the kind provided by StatsBomb, which is the gap addressed here.

Two further gaps motivate the present study. First, although deep-learning and graph-based methods are advancing quickly, comparatively little published work systematically explores the StatsBomb 360° World Cup 2022 dataset as a descriptive baseline. Second, the relationship between advanced event-based metrics and conventional statistics at this tournament has not been characterised in a way that highlights under-recognised contributions. Establishing such a baseline is a necessary precursor to more sophisticated network and graph models of player influence.

The purpose of this study is therefore threefold: (1) to explore and describe individual player performance at the FIFA World Cup 2022 using advanced StatsBomb metrics; (2) to compare advanced metrics with conventional statistics in their ability to discriminate player contribution; and (3) to establish a reproducible computational baseline, including unsupervised playing-style profiles, that can support subsequent research on passing networks and graph-based evaluation.

Materials and methods

Study participants

The units of analysis were individual outfield and goalkeeping players who participated in the FIFA World Cup 2022, which comprised 64 matches contested by 32 national teams. Player and match data were obtained from the StatsBomb Open Data repository, a freely available and openly licensed source of event and 360° freeze-frame data. From an initial pool of 681 players appearing in the tournament, a minimum-playing-time threshold of 180 minutes was applied to ensure that per-90-minute metrics were stable, yielding an analytical sample of 346 players. Players were additionally grouped by playing position (goalkeeper, defender, midfielder, forward) and by confederation (UEFA, CONMEBOL, CAF, CONCACAF, AFC).

Study organization

Data were extracted and processed through a reproducible Python pipeline that adapts the Cross-Industry Standard Process for Data Mining (CRISP-DM) to a computational sport-analytics context. The pipeline comprised five stages: data extraction, data understanding, data

preparation, exploratory data analysis, and unsupervised modelling. Event data, lineups, and 360° freeze-frame data for all 64 matches were retrieved using the statsbombpy interface and parsed into tabular form. The overall research framework is summarised in Figure 1.

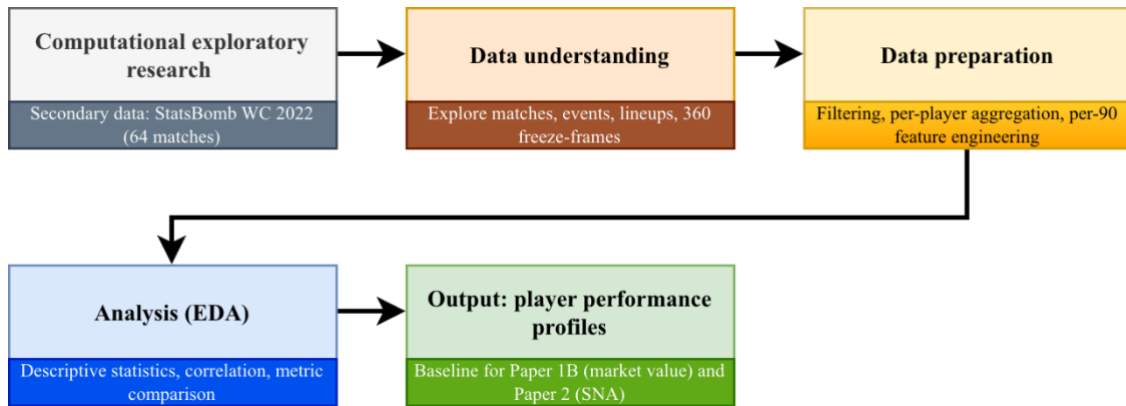


Figure 2. Research framework adapting the CRISP-DM workflow to the StatsBomb World Cup 2022 pipeline

During data preparation, minutes played were computed for each player and match from the starting line-ups, substitution events, and dismissals. Twenty-five advanced performance metrics were then engineered, including passing volume and accuracy, progressive passes and carries, key passes, crosses, through balls, dribbles, shots, expected goals (xG), expected assists (xA), pressures, counter-pressures, interceptions, clearances, blocks, ball recoveries, and duels. Progressive passes and carries were defined following the convention that an action must advance the ball meaningfully toward the opponent's goal, with distance thresholds depending on the zone of origin. All volume metrics were normalised to a per-90-minute basis to allow fair comparison across players with different playing time, and passing accuracy was expressed as a completion percentage. Expected assists were computed by attributing the xG of a shot to the player who delivered the preceding pass.

Statistical analysis

Exploratory data analysis combined descriptive statistics, correlation analysis, and unsupervised clustering. Descriptive statistics (mean, median, standard deviation, and distributions) were summarised overall and by position and confederation. The relationship between advanced metrics and conventional statistics was assessed using both Pearson and Spearman correlation coefficients, with particular attention to the xG-goals and xA-assists relationships. Residual differences between advanced and conventional metrics (for example, xG minus goals per 90 minutes) were used to identify players whose contributions were under-represented by conventional statistics. To recover playing-style profiles, K-means clustering was applied to thirteen standardised per-90 metrics for outfield players, with the number of clusters guided by the elbow criterion, the silhouette coefficient, and interpretability. Principal component analysis was used to visualise the resulting clusters in two dimensions. All analyses were conducted in Python 3.12 using pandas, scikit-learn, matplotlib, and seaborn, and the full pipeline was organised as a sequence of reproducible notebooks.

Results

Dataset overview

The analytical sample comprised 346 players who each played at least 180 minutes, accounting for a total of approximately 113,600 player-minutes. Players averaged around 328 minutes and just under four matches each. The distribution by position group was dominated by defenders (139) and midfielders (99), followed by forwards (73) and goalkeepers (32); a small number of players (3) appeared only as substitutes and could not be assigned a starting position. By confederation, UEFA contributed the largest share of qualifying players (147), followed by AFC (66), CAF (49), CONMEBOL (49), and CONCACAF (35). The distribution of playing time and position groups is shown in Figure 2.

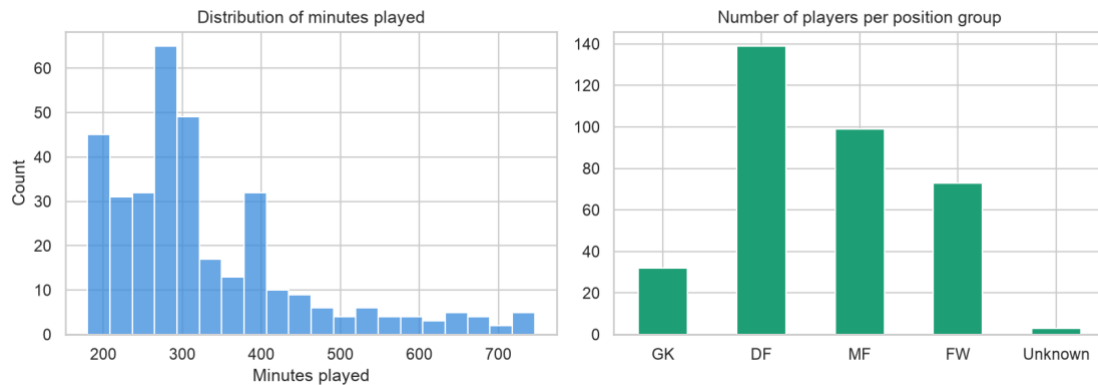


Figure 3. Dataset overview: distribution of minutes played (left) and number of players per position group (right)

Table 1 summarises selected per-90-minute metrics for the analytical sample, illustrating the range of values observed for representative passing, progression, attacking, and pressing indicators.

Table 1. Descriptive statistics of selected per-90-minute metrics (n = 346)

Metric (per 90)	Mean	SD	Min	Median	Max
Passes completed	35.96	18.34	4.0	32.59	138.33
Progressive passes	14.06	6.38	1.5	13.28	40.93
Expected goals (xG)	0.11	0.17	0.00	0.05	0.92
Pressures	10.45	5.81	0.0	10.62	40.50

Note: Full distributions are available in the analytical pipeline.

Per-position performance profiles

Normalised per-90 profiles differed systematically across position groups, as shown in the radar comparison in Figure 3. Defenders recorded the highest progressive-passing values, reflecting the role of central defenders in initiating build-up with long forward distribution. Forwards were clearly distinguished by expected goals and shot-related metrics, as well as by duels contested in advanced areas, whereas midfielders combined the highest pressing volume with strong progressive carrying and creative involvement. These contrasts confirm that different advanced metrics are diagnostic for different positions, rather than any single metric dominating across the pitch.

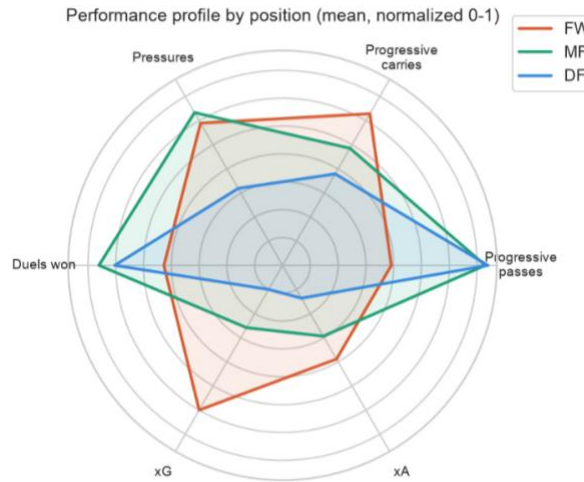


Figure 4. Per-position performance profiles (forward, midfielder, defender) using normalised per-90 metrics

Advanced versus conventional metrics

The comparison between advanced and conventional metrics revealed a marked asymmetry. Expected goals correlated strongly with goals scored (Pearson $r = 0.75$, Spearman $= 0.66$), indicating that the xG model captures finishing output reasonably well at tournament level. In contrast, expected assists correlated only weakly with recorded assists (Pearson $r = 0.22$, Spearman $= 0.28$). This weak association indicates that a substantial proportion of creative contribution, as measured by the quality of chances created, is not reflected in the binary assist statistic, which depends on a team-mate converting the chance. The two relationships are visualised in Figure 4.

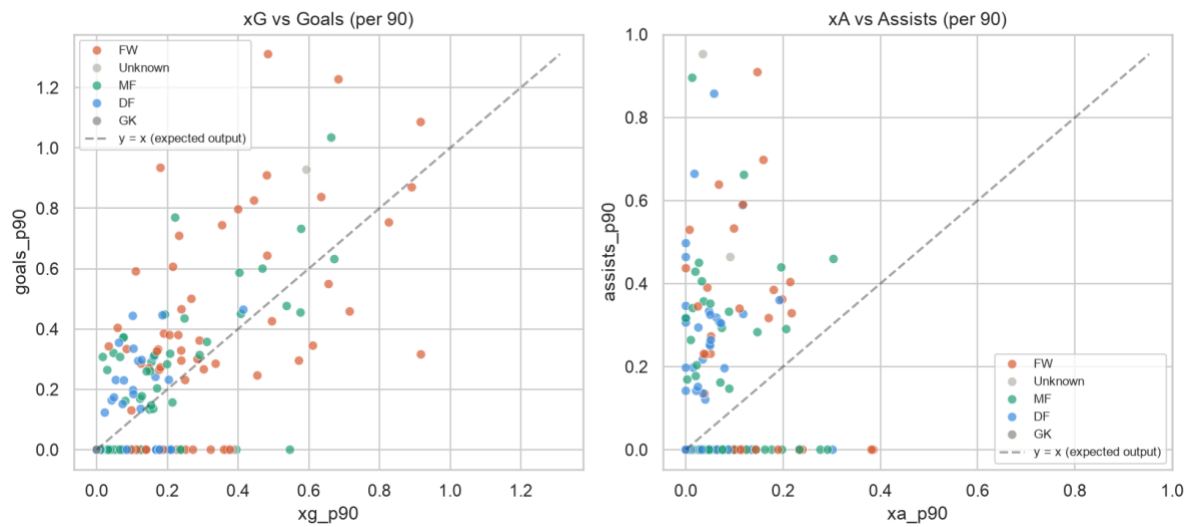


Figure 5. Advanced versus conventional metrics: expected goals against goals (left) and expected assists against assists (right), per 90 minutes

Building on the residuals visualised in Figure 4, Table 2 lists representative players with the largest positive difference between expected and realised output, separately for finishing

(xG minus goals) and creativity (xA minus assists). These players represent tactically valuable contributors whose influence is under-stated by conventional statistics.

Table 2. Representative players with the largest gap between advanced and conventional output (per 90)

Player	Team	Metric	Advanced	Conventional
Lautaro Martínez	Argentina	xG	0.92	0.32
Rodrygo	Brazil	xG	0.55	0.00
Jamal Musiala	Germany	xG	0.38	0.00
Raphinha	Brazil	xA	0.38	0.00
Hirving Lozano	Mexico	xA	0.39	0.00
Kevin De Bruyne	Belgium	xA	0.24	0.00

Note. Values are per-90-minute rates for players meeting the 180-minute threshold.

The correlation structure among advanced metrics is summarised in [Figure 5](#). As expected, progressive passing, key passing, and expected assists were positively associated, as were shooting volume and expected goals, while pressing and counter-pressing formed a coherent defensive-intensity cluster. These patterns provide face validity for the engineered metrics.

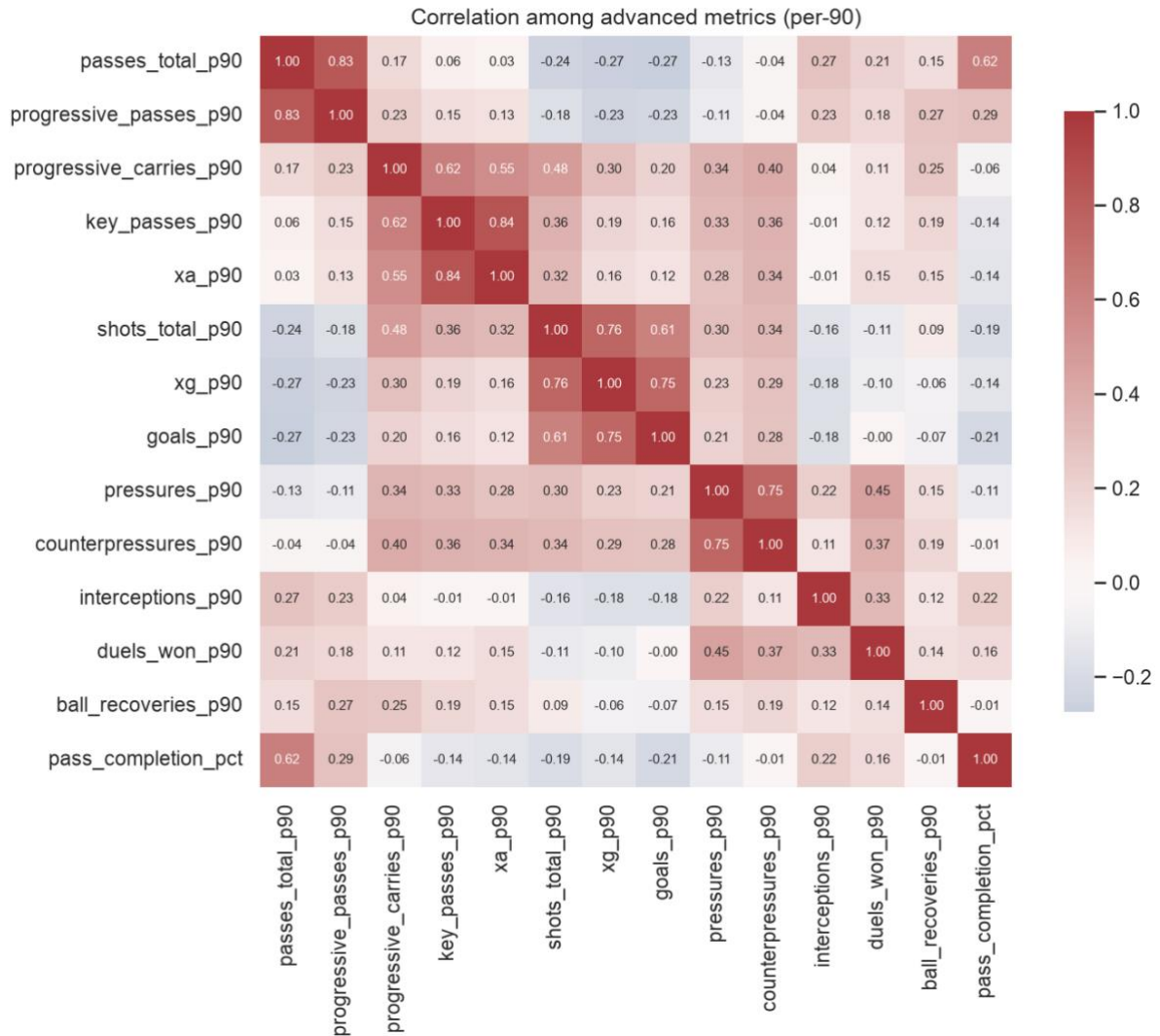


Figure 6. Correlation heatmap among selected advanced per-90 metrics

Cross-confederation comparison

Aggregating metrics by confederation revealed differences in playing style, illustrated in Figure 6. UEFA players recorded the highest progressive-passing volume, consistent with possession-oriented build-up, whereas CONMEBOL players combined high expected goals with the highest rate of duels won. AFC players displayed the highest pressing volume but the lowest expected goals, suggesting an energetic but less efficient attacking profile. While these comparisons are descriptive and influenced by sample composition, they indicate systematic stylistic variation across confederations.

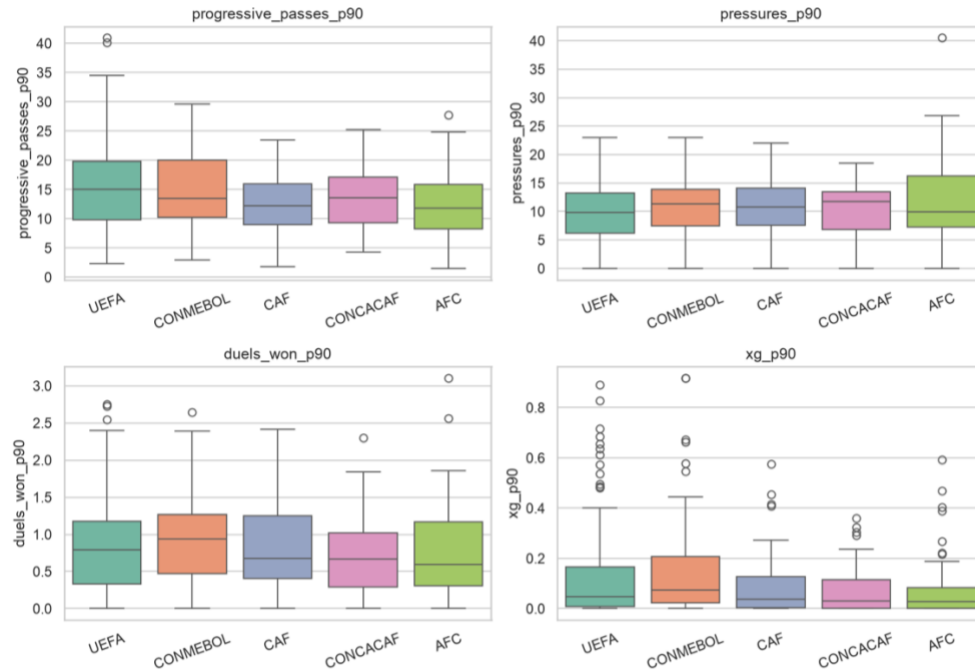


Figure 7. Cross-confederation comparison of selected per-90 metrics (UEFA n=147, AFC n=66, CAF n=49, CONMEBOL n=49, CONCACAF n=35)

Playing-style clusters

Moving from group-level comparisons by confederation to player-level groupings, K-means clustering of standardised per-90 metrics for the 314 outfield players recovered interpretable playing-style groups. Cluster-count diagnostics [Figure 7](#) indicated a statistically optimal solution at a small number of clusters, but a slightly larger solution produced more interpretable, tactically meaningful profiles. The resulting cluster profiles, expressed as standardised metric means, are shown in [Figure 8](#), and their projection onto the first two principal components is shown in [Figure 9](#). The clusters separated creative and progression-oriented attackers from pure finishers, pressing-oriented all-rounders, and deeper defensive players. Importantly, several clusters cut across formal positional labels, grouping forwards and midfielders with similar playing styles together, which demonstrates that data-driven profiles capture stylistic similarity beyond nominal position.

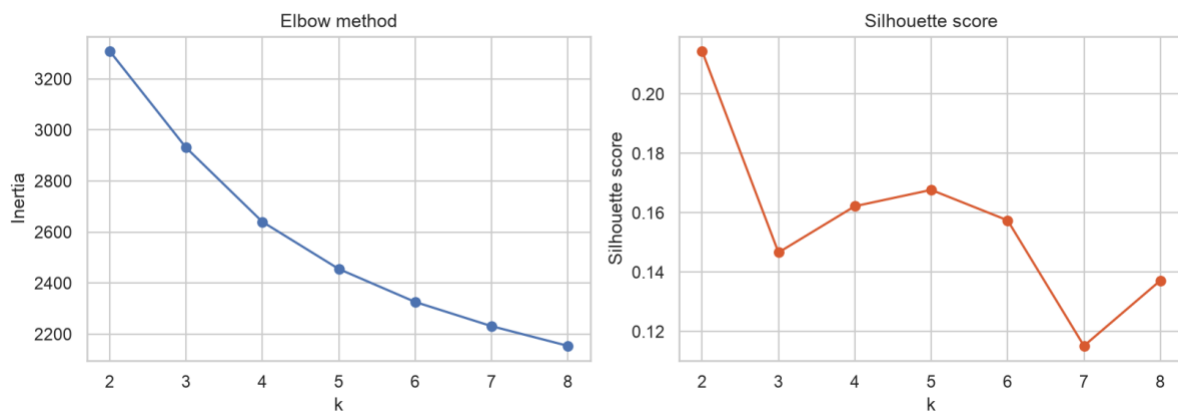


Figure 8. Cluster-count selection using the elbow criterion and silhouette coefficient

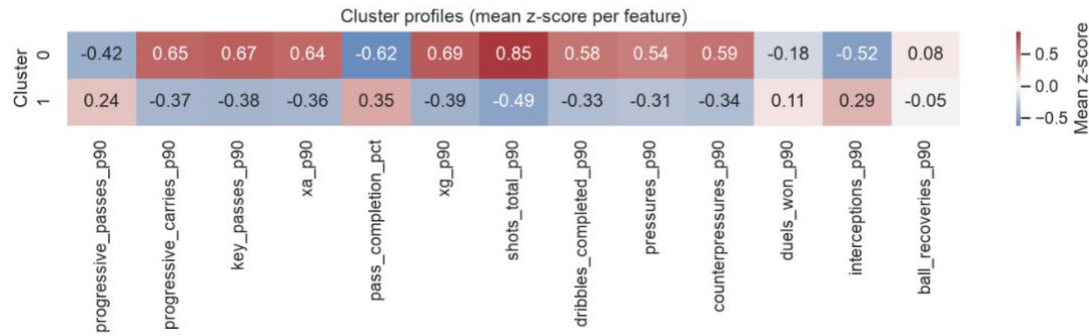


Figure 9. Cluster profiles expressed as standardised (z-score) means of per-90 metrics

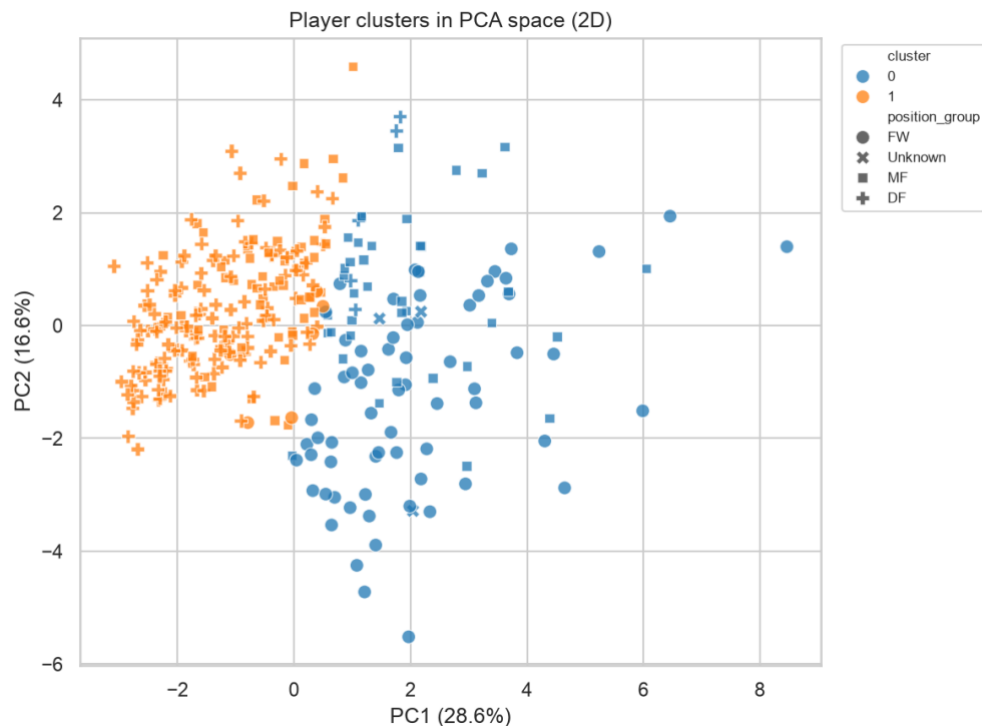


Figure 10. Projection of player clusters onto the first two principal components

Discussion

The central finding of this study is that advanced event and spatial metrics provide a richer and more discriminative description of player performance at the FIFA World Cup 2022 than conventional box-score statistics. The strong association between expected goals and goals contrasts sharply with the weak association between expected assists and recorded assists, indicating that creative contribution in particular is poorly captured by conventional counting statistics. This is consistent with the broader literature, which argues that shot-centric and outcome-focused metrics undervalue build-up and off-ball play, and that expected-threat and possession-value approaches are needed to look beyond shots (Corsaro et al., 2025; Narayanan & Pifer, 2023). It also aligns with evidence that running-based and outcome-based indicators correlate only weakly with broader measures of player quality at the World Cup (Kılıcı et al., 2025).

The identification of players whose advanced metrics substantially exceed their conventional output has a meaningful real-world counterpart. Because the present analysis is being conducted during the FIFA World Cup 2026, the subsequent trajectories of several players flagged as under-represented in 2022 can be observed retrospectively. Lautaro Martínez, who recorded the largest gap between expected goals and goals in the sample, subsequently became the captain of his club and was recognised as the leading forward in his domestic league, having struggled with injury during the 2022 tournament. Jamal Musiala, the only player to appear among both the finishing and creativity residual leaders, was widely identified by expert observers as an exceptional talent in 2022 before his output statistics reflected this, and he developed into a central attacking figure for his national team. Raphinha, who recorded no assists in 2022 despite a high expected-assist value, subsequently produced one of the most productive creative seasons in European club football. These trajectories provide qualitative, illustrative support for the claim that advanced metrics captured latent quality that conventional statistics had obscured. A cautionary counter-example is provided by Rodrygo, who also showed a large expected-goals residual in 2022 but was subsequently unavailable for selection in 2026 due to serious injury, underscoring that these metrics describe tactical potential at a point in time rather than guaranteeing long-term outcomes.

The position and confederation analyses reinforce the value of a multi-metric approach. The finding that defenders lead progressive passing while midfielders dominate pressing and progressive carrying demonstrates that no single metric suffices to evaluate players across roles, echoing arguments that tactical behaviour is best described through multiple complementary indicators (Goes et al., 2021; Teixeira et al., 2025). The unsupervised clustering further showed that data-driven playing-style profiles can transcend formal positional categories, consistent with work using tracking-derived tactical features and representation learning to characterise style (Goes et al., 2021; Nakahara et al., 2023).

These results also clarify the position of the present study within the wider analytical landscape. While expected-goals models and their refinements remain valuable and well-calibrated tools for shot evaluation (Anzer & Bauer, 2021; Bandara et al., 2024; de-la-Cruz-Torres et al., 2025; Mead et al., 2023), they are inherently limited to the shooting phase. Network- and graph-based methods are increasingly proposed to capture interaction structure, build-up, and defensive organisation that shot-based metrics omit (Alves et al., 2025; Chacoma, 2025; Ievoli et al., 2021; Lee et al., 2025; Zhou et al., 2023). The descriptive baseline established here, including the engineered advanced metrics and the playing-style clusters, provides a natural foundation for such graph-based extensions, and recent work demonstrates the promise of graph convolutional and multi-agent approaches for football player evaluation (Majeed et al., 2025; Raabe et al., 2022).

The standardised, player-level features developed here may also be of practical value to the Indonesian football-analytics literature reviewed earlier. Studies using C4.5 decision trees to predict Champions League outcomes (Tandian et al., 2019) and ensemble methods to predict BRI Liga 1 results (Hidayat et al., 2024) have so far drawn on aggregated, match-level statistics, while FP-Growth analyses of the Indonesian national team's ball distribution have relied on manually annotated video (Ardiantoro et al., 2023). The per-90 advanced metrics and playing-style clusters proposed here could provide richer, automatically extracted player-level inputs for such predictive or association-rule models, narrowing the gap between Indonesian football-analytics research and the StatsBomb-based international literature.

Several limitations of this study should be acknowledged. First, the analysis is confined to a single tournament and is therefore cross-sectional and descriptive rather than longitudinal or causal; findings may not generalise to other competitions or seasons. Second, the minimum playing-time threshold of 180 minutes, while necessary to stabilise per-90 estimates, excludes players whose limited appearance time reflects injury or squad rotation rather than low quality, and may introduce selection bias toward players from teams that advanced further in the tournament. Third, K-means clustering is sensitive to initialisation and to the chosen distance metric, and the number of clusters was selected partly on interpretability grounds rather than purely on statistical criteria; alternative clustering approaches such as hierarchical clustering or Gaussian mixture models may yield different groupings. Finally, the retrospective player trajectories discussed above are illustrative observations rather than a formal longitudinal validation and should be interpreted accordingly.

Conclusions

This study established a reproducible computational baseline for evaluating individual player performance at the FIFA World Cup 2022 using StatsBomb event and 360° spatial data. Across 346 players meeting a minimum-playing-time threshold, advanced per-90 metrics provided a more discriminative description of contribution than conventional statistics, most strikingly in the weak correspondence between expected and recorded assists. Position and confederation profiles differed systematically, and unsupervised clustering recovered interpretable playing-style groups that transcended formal positional labels. The retrospective trajectories of several players identified as under-represented in 2022 offer qualitative support for the validity of these advanced metrics. Taken together, the findings demonstrate that advanced event and spatial metrics complement rather than replace conventional statistics, and they provide a foundation for subsequent network- and graph-based evaluation of player influence. The main limitations are that the analysis covers a single tournament and is cross-sectional and descriptive rather than causal, and that the retrospective validation is illustrative rather than a formal longitudinal test. Future work will extend the pipeline to passing-network analysis and graph neural networks, and to additional tournaments for external validation.

Acknowledgment

The authors gratefully acknowledge StatsBomb for making the event and 360° freeze-frame data publicly available under an open licence, which made this research possible.

Conflict of interest

The authors declare no conflicts of interest.

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Cite this article as:

Permana, I. Ngiliyun, A. Wahyuni, D. (2026). A Computational Exploration of Football Player Performance at the FIFA World Cup 2022 Using StatsBomb Event and 360° Spatial Data. *Indonesian Journal of Physical Education and Sport Science (IJPESS)*, 6(3), 477-490. <https://doi.org/10.52188/ijpess.v6i3.2260>