National College of Ireland

Decision-Making Under Pressure: A Multi-Level Analysis of Tactical Adaptation and Passing Intelligence in Football

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MSc Project Submission Sheet

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Decision-Making Under Pressure: A Multi-Level Analysis of Tactical Adaptation and Passing Intelligence in Football

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Abstract

In professional football, decisions about substitutions can have a significant impact on games and are usually made under pressure and with very little time. As of yet, most current analytics frameworks remain mostly descriptive and retrospective. This study proposes a combination of three models for the detection of player performance using the Ghost Opportunity Index (GOI) for decision-making quality, the Formation Drift Index (FDI) for any structural changes, and the High Pressure Expected Impact (HPEI) for player performance. Using open-source StatsBomb event data from FC Barcelona's La Liga games, these indicators were combined into a deterministic, easy-to-understand substitution engine that was tested through time-series and player-level analysis. This model alerts managers on average 11 minutes earlier than the current substitution methods, making real-time substitution decisions more effective. The results demonstrate that GOI and FDI go up during the last few minutes of a game, indicating that decision quality declines while tactical stability increases. HPEI also successfully separates players who can handle pressure from those who cannot. The study shows that it is possible to make interpretable, prescriptive substitution decisions using only event data. Full testing of the model was limited by missing lineup data and fatigue indicators.

Keywords – Football analytics; Substitution decision support; Expected Threat (xT); Tactical drift; Performance under pressure, Ghost Opportunity Index

1 Introduction

Small strategy choices have a significant impact on the outcomes of football games, especially in competitive leagues such as La Liga. More clubs are adopting data-driven strategies, asking analysts not only for post-match feedback but also to provide predictive frameworks for real-time decision-making.

Current expected threat (xT) models created by (Fernández *et al.*, 2019; Hassani *et al.*, 2025), predicative danger models, passing networks and geographical analysis done by (Fernández and Bornn, 2018) are mostly still descriptive and reactive, rather than proactive in real-time, pressure situations. Space-value models quantify spatial value but do not address tactical instability or fatigue during matches (Pena and Touchette, 2024; Bortnik *et al.*, 2024) and are not often used in well-organised, decision-support systems.

Background and Motivation

Most tactical decisions made in real-time are still manager-driven and subjective, especially when it comes to substitutions. Under pressure, coaches must evaluate players' fatigue, tactical instability, and deteriorating technical performance, often in a matter of seconds, without quantitative data. Studies on models such as expected threat, pressure measures, and formation changes have concluded that they play a significant role in substitutions, but no effort is currently being made to integrate these models into a substitution recommendation system.

The goal of this project is to close this gap by using open StatsBomb event data from FC Barcelona's La Liga games to create a multi-level substitution support system. These performance indicators include the Ghost Opportunity Index (GOI). This local counterfactual metric evaluates decision quality by comparing the xT gain of an executed pass to the best available alternative pass in the player's surrounding spatial neighbourhood. The Formation Drift Index (FDI) is a measure that identifies changes in teams during a game formation's baselines across 5-minute time windows, and the High Pressure Expected Impact (HPEI) is a pressure-weighted measure of the expected value of a player's on-ball actions, combining xT with model-predicted pass success probabilities. Adding these models together can provide a numerical value for performance.

Research Problem

Although network-based xT techniques have aided in performance evaluation in the past (Decroos and Davis, 2020; Fernandez and Bornn, 2018) and the importance of geographical models, pressure measures and network changes have been emphasised in football analytics literature, little effort has been made to integrate these elements into a single framework to support predicative decision-making or researched on how it could assist real-time substitution decisions.

Most studies to date have focused on success after the fact rather than helping people plan. Both the dynamic xT model developed by (Hassani *et al*., 2025) and the pressure or pass success model developed by (Pena and Touchette, 2024) and (Bortnik *et al*., 2024) are useful, but neither incorporates formation drift or decision-making into their substitution derivations.

In professional football, substitutions result from an unstable team plan, loss of possession, or technical underperformance (Pan *et al*., 2023). However, current analytics tools do not identify these patterns in a way that provides quick assistance to a coach. Presently, there are no active models that combine drift decision-making and pressure to create substitution.

Research Question

Can formation drift, pressure-weighted performance, and decision-making metrics predict optimal substitutions for FC Barcelona during La Liga matches?

Research Objectives

We established four goals to address the research topic of this study:

- Discover better techniques for space-time football analytics and substitute modelling.
- Develop and construct an integrated framework based on xT, GOI, FDI, and HPEI using StatsBomb event data.
- Install a recommendation engine for deterministic substitutes that evaluates players over rolling time periods.
- Finally, compare the system with actual FC Barcelona replacements by analysing player-level statistics, match timings, and other factors.

Contributions and Limitations

Three main models will be used to create a uniform, easy-to-understand substitute recommendation engine built on deterministic rule-based logic rather than machine learning. The creation of GOI, a novel micro-decision-value metric aligned with xT spatial opportunity modelling, that extends the logic of xT-based action valuation (Hassani *et al*., 2025) by comparing an executed pass to the best available alternative within its spatial neighbourhood, is one of the research's main accomplishments. There is a new Formation Drift Index that uses positional baselines instead of clustering methods to measure tactical structure in real time.

The last model is a pressure-weighted HPEI metric that measures the effectiveness and dependability of decisions made under pressure, building on prior work on pressure modelling (Pena and Touchette, 2024) and pass-success prediction (Bortnik *et al*., 2024). Some limitations before the work starts are that the lineup data is currently incomplete for players starting on the bench, and there are no real-time scores with GPS tracking to show pressure or fatigue.

Paper Structure
The structure of this document is as follows: Section II addresses relevant research, analysing prior research results and discussing their relevance to the current study report. Section III will address the application of the suggested research methodologies to resolve the study issue. Section IV addresses the Design specification; Section V outlines the implementation of the experiment; Section VI evaluates the analysis; Section VII discusses the conclusions and findings; and Section VIII presents the references utilised in this study.

2 Literature Review

2.1 Metrics for Player Performance Modelling

To date, football analytics has offered helpful but limited insights into the significance of player actions by focusing primarily on event frequencies, such as pass counts, possession time, and shot totals. This flaw creates the need for probabilistic action-value models. (Fairchild *et al*., 2018) demonstrated that expected goals (xG) enhance match outcome prediction relative to raw shot counts, using logistic regression on shot location data. This technique, although repeatable and straightforward, was not helpful for the buildup play phase and applied only to shots. A study conducted by (Spearman, 2018) used tracking data to provide evidence that the likelihood of a shot increases when avoiding defenders and also included defensive pressure in the modelling.

(Fernández *et al*., 2018) developed an Expected Threat (xT) model that is another possible choice to that of a shot-based model that looks at the change in passing direction across a pitch divided into blocks. This technique examines how the ball's movement can affect the likelihood of scoring. The results showed that certain areas on the pitch have a greater chance of a next shot than looking only at passes. As this relies on the transition frequency and could be influenced by tactical bias, this xT presents problems.

By assessing the impact of each action on creating scoring opportunities or on conceding goals, VAEP (Decroos *et al*., 2020) expanded on the standard action-value models to include all on-ball events and assigned a value to every action. This study did have drawbacks in that there is a need for a lot of feature engineering, and that every action was calculated independently, rather than as part of a long sequence of events that came before and after.

Additionally, counterfactual modelling has become popular. (Le *et al*., 2017) created a "ghost passes" model that uses nearest-neighbour techniques to forecast optimal passing decisions. Even if their method can detect when a player did not choose the best possible action, it can not evaluate team tactics and is constrained to simple decision rules. Although the results are still primarily qualitative, (Bialkowski *et al*., 2014) used player embeddings to simulate alternative action sequences.

Together, these investigations show how basic event counts gave way to probabilistic, comprehensible value models. However, the pressure environment, decision optimality, and team structural dynamics necessary for real-time tactical support are not included in any of the current studies. This drives the current study, including the Ghost Opportunity Index (GOI) and the High Pressure Expected Impact (HPEI).

2.2 Tactical and Team-Level Analytics: Passing Networks and Formation Modelling

Group behaviour and how spaces are organised provide insight into team planning, and passing networks have given us valuable tools for this. (Cintia *et al*., 2015) used graph centrality metrics to measure player impact and found links between match dominance and centrality. Passing networks, though easy to set up and use, often fail to capture dynamic movement (Gudmundsson and Horton, 2017).

By analysing motif frequencies in passing networks, (Li *et al*., 2025) demonstrated how stylistic trademarks, such as Barça's possession triangles, help teams stand out from one another. However, motifs do not convey real-time tactics; they only represent structural patterns.

Tracking data cases makes it feasible to create more complicated formation models. (Bialkowski *et al*., 2014) successfully employed k-means clustering on player positional heatmaps to automatically discern formations, but constant monitoring is required; this is not possible with publicly available statistics. (Carpita *et al*., 2020) used role-based clustering to estimate players' dynamic locations, but it too required manual labelling and substantial spatiotemporal data.

These improvements were summarised in (Gudmundsson and Horton's, 2017) assessment, which noted that while tracking-based formation approaches capture tactical structure, they usually overlook temporal drift, or how formations change over the course of a match.
Since event-based datasets lack uniform placement and there is no way to tell if a shape is unstable just by looking at event placements, a gap needs to be filled. The FDI aims to close that gap by making structural changes without having to buy expensive tracking gear.

2.3 Counterfactual Analytics: Transitioning from Ghosting Models to the Ghost Opportunity Index

Counterfactual modelling does not just describe events; it also tries to predict "What could have happened?" (Le *et al*., 2017) used spatial algorithms to identify the best possible passes and coined the term "ghosting" in football. Their model, although clever, has a constantly changing base sum and performs poorly in full-match review. It took good tracking data for their model to work, but it used ghosting and deep imitation learning to guess full routes.

Using player embeddings, (Decroos *et al*., 2020) generated counterfactual sequences that provided richer representations, but required neural architectures and sizable datasets that are not typically available for open event data.

Since xT's state-based valuation gives value to positional states rather than just acts, it is especially well-suited for counterfactual analysis. This makes it easier to compare actual passes with potential alternatives. Building on this, the current work introduces the Ghost Opportunity Index (GOI), which operationalises decision-optimality using local xT-based alternatives. In contrast to previous work, GOI is utterly compatible with sparse event data and offers consistent aggregates at the individual and team levels.

2.4 Substitution Analytics and Decision Support Systems

There are not many studies on the substitute approach. When (Pawlowski *et al*., 2010) examined the timing of substitutes, they discovered that earlier offensive substitutions were associated with better outcomes. However, rather than being analytically generated, substitution causes were viewed as external decisions. In their evaluation of match context as a factor influencing substitution patterns, (Wright *et al*., 2011) found that trailing teams tend to make earlier substitutions. However, these models do not account for player-level tactical instability or decision quality.

(Baadi *et al*., 2025) use player characteristics, score differentials, and fatigue indicators to predict substitution outcome using machine learning techniques. Their approach did not specify who or when should be substituted; however, it did categorise outcomes as good or bad. No previous work has combined tactical drift with HPEI, pressure-weighted action value with GOI, or counterfactual decision quality and real-time evaluation based on xT into a single engine for substitution. This study closes that gap.

2.5 Machine Learning and Reinforcement Learning for Decision Optimization

Both result prediction and tactical modelling have benefited from machine learning. (Sarkar *et al*., 2023) created a passing sequence model using RNNs, but the model could not explain why it predicted certain outcomes or which tactical factors mattered most, and it explained that it needed patiotemporal player tracking to improve. The study of (Liu and Zou, 2021), a machine learning model, could not work due to the small sample size that it had.

(Brooks *et al*., 2016; Bassek *et al*., 2019) used movement patterns in NBA and football tracking data, showing that clustering movements enabled the model to automatically detect player roles and movement styles from the data without manual labelling. Although this research relies on high-resolution tracking that is not available in publicly available datasets, making the reproduction of results difficult, it still demonstrates strong modelling power.

RL is now being applied in sports and not just in robotics or games like chess. (Mohandas *et al*., 2023) used RL to optimise handball substitutions by treating substitution decisions as sequential decision problems, and (Biro and Walker, 2022) used RL in football-play by letting the RL model choose which tactical play to run next. Using RL on StatsBomb data, (Guo *et al*., 2024) simulated micro-action value in football, producing optimistic results but still only allowing for action-level evaluation.

No research has integrated pressure, tactical organisation, and decision quality in RL or ML for substitute recommendation. The Substitution Recommendation Engine presented in this study is inspired by RL decision-making frameworks (reward comparison and state evaluation), but, due to data limitations, it applies them deterministically.

2.6 Summary and Research Gap

According to the literature, significant progress has been made in the areas of formation modelling, outcome forecasting, counterfactual prediction, and action-value metrics (xT, VAEP). However, there are four main drawbacks to current methods:

Gap 1	No real-time action evaluation that is weighted by pressure, but the HPEI fills the gap left by current models' failure to incorporate defensive or psychological pressure into continuous action-value calculations.
Gap 2	Event data is not used to quantify tactical instability, but Real-time drift is not measured by formation modelling studies, which necessitate tracking data. The first event-based formation instability statistic is the FDI statistic.
Gap 3	The quality of counterfactual decisions remains micro-level, and the Ghosting models do not incorporate lost value into tactical analysis or aggregate it. By offering counterfactual decision profiles at the team and player levels, GOI closes this gap.
Gap 4	No system for integrated substitution decision support. Substitution studies do not account for multi-factor tactical assistance; instead, they focus on time or outcome classification. There is currently no research that combines tactical changes, action-value modelling, and counterfactual decision-making into a logical framework for substitution.

By integrating GOI, FDI, and HPEI, this study offers the first interpretable, event-data-driven substitution suggestion system.

3 Methodology of Research

The methodology in this study used the CRISP-DM model to build a data-driven substitution system. This model breaks the project into six phases: business understanding, data understanding, data preparation, modelling, evaluation, and deployment. This section gives details on how each section was created.

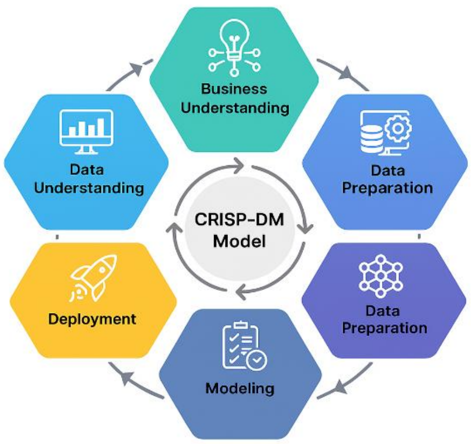

Figure 1. Methodology overview

3.1 Business Understanding

Professional football is one of the most popular sports worldwide and generates significant revenue, which puts pressure on teams to perform well. One way to optimise team performance is to calculate the optimal time for substitutions.

3.2 Data Understanding

3.2.1 Source of Data

All data for this study comes from StatsBomb datasets, open-source data freely available. The data comes in the form of a match-event-level record created for each action during a match. The two files collected were the event files, which contain each player's events as the match progresses, and the lineup data file, which contains teams and dates.

3.2.2 Characteristics of the Data

The event data contains passes, carries, shots, defensive actions, substitution events, player identification, and the match time. Each of these events comes with timestamps and coordinates. Substitution events come in the form of "Sub On/Sub Off" events, and the player identifiers are used to group the HPEI and GOI. These characteristics of the data form the basis for the development of the xT, HPEI, FDI and GOI.

3.3 Data Preparation

3.3.1 Parsing and Cleaning

The data from StatsBomb contains complicated nested JSON structures. These were downloaded from StatsBomb and stored locally. A custom Python script was developed to extract the data and flatten it into an event-per-row dataframe. The substitution events were extracted and linked to match timelines by comparing the event minutes with the substitution records. The steps that were used for cleaning the data once it was extracted are listed below:

Table 1. Data Cleaning

Steps	Task
1	Remove the events that do not have coordinates
2	Convert the coordinates to numeric values
3	Transform the pitch dimensions to a 120 x 80 scale
4	Remove the duplicated rows
5	Assign unique match identifiers.

3.3.2 Transformation and Normalisation

To support the modelling of locations and their interactions, all coordinates had to be normalised to the same pitch frame. This means creating a grid frame of the pitch to derive the distance and angle of passes, distinguishing between difficult and non-difficult shots. The pressure indicators had to be converted to binary fields: “1” for Yes and “0” for No. Create a rolling window for analysis, so the minutes are rounded to fit it. All these fields were stored in CSV files for easier reproduction.

3.4 Model Development

This study uses four main models to compute and analyse.

3.4.1 Expected Threat Measurements (xT)

A 12x8 grid was computed and then applied to all the events. For each grid cell, there were three derivations. The number of transitions into the following zones, the number of ball losses and the number of shots taken. These derivations are then combined to find the player impact measurement. The formulation of this algorithm is then:

$$\Delta xT = xT(\text{end}) - xT(\text{start})$$

This measurement is used in the GOI, HPEI and the substitution evaluation.

3.4.2 High-Pressure Expected Impact (HPEI)

A gradient-boosting model (XGBoost) estimates the probability of passing success. The most important features for the XGBoost classifier are Distance, Angle, pressure and time. First, the expected impact is calculated, and then a pressure adjustment is made. Below, we give the derivations.

$$Expected\ Impact = P(success) \cdot \Delta xT$$

$$HPEI = Expected\ Impact \cdot (1 + \alpha \cdot under\_pressure)$$

where α is equal to 0.75

3.4.3 Formation Drift Index (FDI)

The FDI model measures the instability in tactical movements. The measurements include player movements in 5-minute windows, the baseline for team formation calculated in the first 10 minutes, and the distance of the drift. This model is derived as follows:

$$drift = \sqrt{(x - x_{base})^2 + (y - y_{base})^2}$$

where x, y are the average position in the current 5 minute window and x_{base}, y_{base} is the baseline positions from the first 10 minutes

3.4.4 Ghost Opportunity Index (GOI)

The derivation of the GOI Model uses a trained pass-success model, simulates ghost passes, and estimates xT outcomes. For each pass event, the model identifies the nearest possible option to pass to. Calculate the xT change for the possible option and compare it with the actual change that happened. A higher GOI value indicates a bigger missed opportunity. The formula is given below:

$$GOI = xT(ghost\_target) \times x\mathrm{T}(actual\_target)$$

3.4.5 Substitution Recommendation Engine

The final substitution system uses the combination of these models to determine who needs to be replaced.

3.5 Statistical Techniques and Evaluation

3.5.1 Statistical Methods

Several computational techniques were applied to evaluate measurements for each layer of the research. For fatigue detection, a rolling time window method was used. Time-series analysis was applied to assess FDI stability. Gradient boosting was done to estimate the pass success rate. Error distribution was done for the GOI, and value iteration was applied for the xT modelling.

3.5.2 Evaluation

To evaluate the model's success, an evaluation was done per player across all matches. Critical intervals were set to identify where pressure and fatigue are at their highest levels, and then the HPEI, GOI spikes, and drift formation. Graphs and figures will be used to present the analysis visually. This will be in the form of heatmaps, box plots, and scatter plots.

3.6 Deployment

The final stage of CRISP-DM ensures the system is reproducible and accessible. The entire pipeline is implemented in a modular Jupyter Notebook with clearly separated code cells, Markdown annotations and visualisations (xT grid, xT trajectories, substitution impact charts). Deployment produces the xT grid, XGBoost model file, per-player xT summary tables, a substitution recommendation file (CSV) and figures.

4 Design Specification

4.1 System Architecture Overview

This system consists of five major components, as depicted in Figure 2. The pipeline comprises a set of Jupyter notebook files that must be run in sequence.

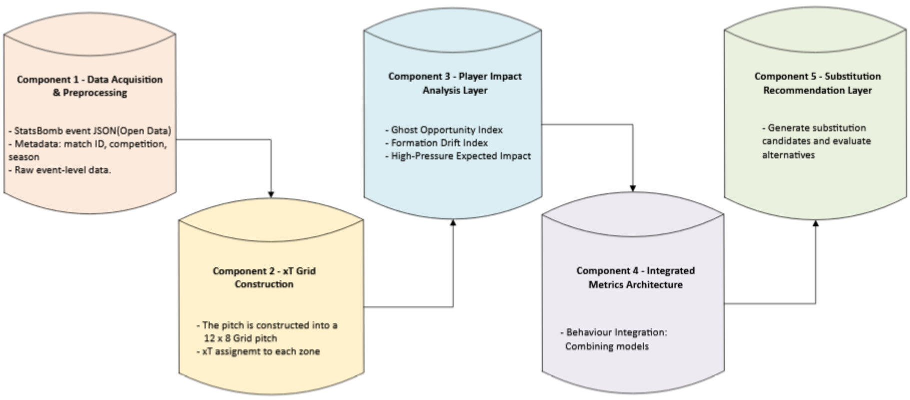

Figure 2. System Architecture Overview

4.2 Data Acquisition & Preprocessing

During this component, the JSON files are extracted and flattened into a structured CSV. The coordinates are normalised into a standard 120 × 80 pitch. Because not all pitch sizes are the same, Statsbomb data are encoded to a 120 × 80 coordinate system. If the data is not normalised to this standard, the alignment between the indicators may be off. The main element is to handle the missing or incorrect data. Upon completion, flags are created for use during analysis. These flags are generated to identify fields such as passes, carries, under-pressure players, and the angle to the goals. Once these flags have been created, we remove rows with invalid coordinates and create a simplified dataset for downstream analytics.

4.3 xT Grid Construction

Unlike traditional xT models (transition matrix + value iteration), this project uses a simplified fixed-grid xT surface generated in the Grid notebook. The output created is an xT 12 x 8 grid model. This is done because the pitch is normalised, so that each area consists of a 10 x 10 zone. This grid provides the value of the receiving location, the value of the current location, and the local "best option" neighbourhood for GOI. This grid helps derive the xT calculation, the GOI, and the HPEI impact estimation. The figure below shows how the grid is broken up.

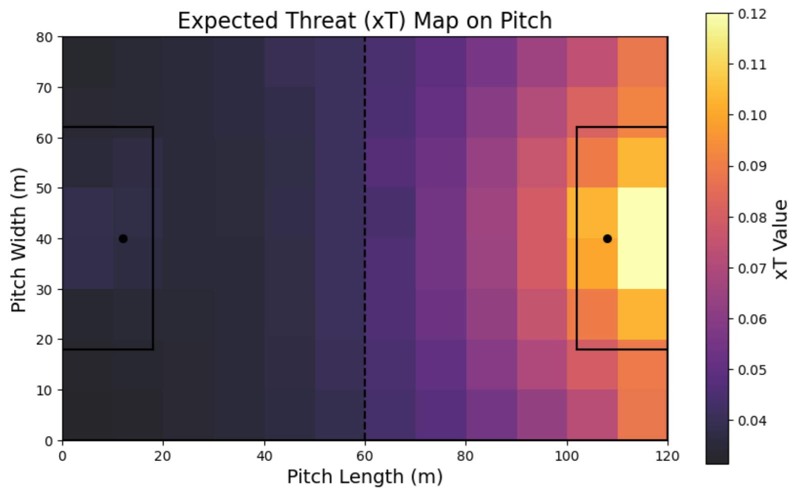

Figure 3. Grid Construction

4.4 Player Impact Analysis Layer

This layer consists of three independent but complementary models, each created in a separate notebook.

4.4.1 GOI: Ghost Opportunity Index

GOI checks how good a decision is by comparing the xT chance of a pass with the best possible target in the player's local area. To derive this, a 3×3 neighbourhood of the xT grid is evaluated to find the best possible alternative passes in that area. (Le *et al.*, 2017) showed this to be a successful method to find the players who often have short or medium-range options. Comparable methodologies have been utilised in football ghosting models (Le *et al.*, 2017). The model then employs a trained pass-success estimator to examine potential ghost choices. A higher GOI value means that more opportunities were missed.

4.4.2 FDI: Formation Drift Index

The FDI measures tactical structure changes over time. The design's characteristics include creating a baseline formation in the first 10 minutes of the match. According to (Pan *et al*., 2023), this is the best time to use, as this shows the intended structure before opponents start changing their shape or fatigue sets in. Using a 5-minute rolling window, the drift calculation takes the mean distance from the baseline coordinates. The 5-minute rolling window is commonly used in analysis because it offers a good balance between sensitivity and measurable stability (Gudmundsson and Horton, 2017). Moreover, this produces player- and team-level drift summaries. This gives the FDI the ability to capture structural drift and fatigue.

4.4.3 HPEI: High-Pressure Expected Impact

The HPEI measures the threat and assigns it a weight based on pressure. The characteristics of this derivation are the pass success probability obtained from the pre-trained XGBoost, multiplied by 0.75. XGBoost demonstrated superior predictive stability and spatial feature sensitivity because of its strong performance on structured data, as past studies have shown it outperforms other machine learning models (Bortnik *et al*., 2021).

The pressure-weighted value of alpha is 0.75 and was chosen because player fatigue, tactical breakdowns, or pressure spikes can change within minutes, so the model should respond strongly. Most sports decision-support models select α between 0.6 and 0.85, so 0.75 falls in the middle.

4.5 Integrated Metrics Architecture

Although FDI, HPEI, and GOI are kept as separate CSV files, they are combined for substitution analysis. In Table 2, each metric depicts distinct behaviour:

Table 2. Metrics architecture

Metric	Measures	Indicates
GOI	Missed decision value	Poor decision-making, bad option selection
FDI	Tactical spacing drift	Fatigue, structural breakdown
HPEI	Threat generation under pressure	Composure, press resistance

4.6 Substitution Recommendation

This is the final component that combines all metric outputs. The system identifies players performing below the team's ranking, players drifting from formation, and players not performing well under pressure. Suitable substitutes are then recommended based on their GOI, FDI and HPEI scores.

4.7 System Assumptions

The system's design accounts for several factors. Only on-ball events are used to predict players' positions, and, because the lineup data is incomplete, minutes played are based on players observed at those events. Only rule-based logic is used to make substitution recommendations; machine learning is not used. The xT model does not use dynamic value iteration; it uses static value iteration instead.

5 Implementation

The implementation of this project involved creating several Jupyter Notebook files to transform raw JSON data into player assessments to produce a substitution system.

5.1 Development Environment and Tools

The environment used for the analysis is Jupyter Notebook. Python is the primary programming language used for this analysis. It uses the most common libraries, such as NumPy and Pandas for data manipulation, and Matplotlib and Seaborn for visualisations. Joblib is used for loading trained models and sklearn utilities for feature scaling and probability estimation. Statistical Files are saved as CSV files, and the figures/graphs are saved as PNG images, enabling downstream evaluation and integration into reporting.

5.2 Data Transformation Outputs

The system converts the raw StatsBomb JSON files into a single, structured dataset, events_compact.csv, which is the final output of this stage. It contains the normalised coordinates (120 × 80 pitch), pass, carry, pressure, and dual events. Also included are team, player, minute, and match identifiers, along with features such as angle-to-goal and pressure flags. This file serves as the standard input to all following analytical modules.

5.3 Grid Value Model Output

The Grid model creates a 12 x 8 grid that is used in the GOI and HPEI. This model is saved as a NumPy binary file. The model also gives visualisations of the xT distribution.

5.4 Player Impact Modules

The outputs produced with the GOI Notebooks contain data of players' GOI values, the teams' GOI values, as well as all the passes with GOI values. GOI histogram, scatterplots and error charts are generated in this model. The outputs produced by the FDI notebook contain data on players' FDI as well as teams' FDI. The notebook also contains formation drift plots and a team-level drift plot. The outputs produced with the HPEI Notebooks contain data on players' HPEI values, the teams' HPEI values, as well as all the passes with HPEI. This notebook also creates HPEI vs xT scatterplots and pressure maps.

5.5 Substitution Recommendation System Outputs

The substitution model combines the three core modules into a substitution recommendation system. The outputs created in this notebook include a CSV file containing all players who need to be substituted, the GOI, FDI, and HPEI indicators, and the recommended substitutes. Visuals include risk curves, radar charts, time-series dips, and explanation overlays.

5.6 Summary of Implementation Outputs

Table 3. Outputs created for analysis

Module	Outputs
Extraction	events_compact.csv
xT Grid	xT_grid.npy and grid visualisations
GOI	passes_with_goi.csv, player_goi.csv, team_goi.csv, visualisations
FDI	player_fdi.csv, team_fdi.csv, drift plots

HPEI	passes_with_hpei.csv, player_hpei.csv, team_hpei.csv, visualisations
Substitution Engine	substitution.csv, evaluation plots

6 Evaluation

This section presents the results of the analysis of the three models developed in this project: decision quality, tactical changes and high-pressure performance, as well as the substitution system.

6.1 Evaluation of the Ghost Opportunity Index (GOI)

6.1.1 GOI Distribution

The GOI calculates missed opportunities by comparing them with the actual passes. In Figure 4, the Barcelona dataset shows a strong right-skewed distribution, consistent with previous studies. Most decisions show minimal missed opportunities, while only a small section shows high missed values.

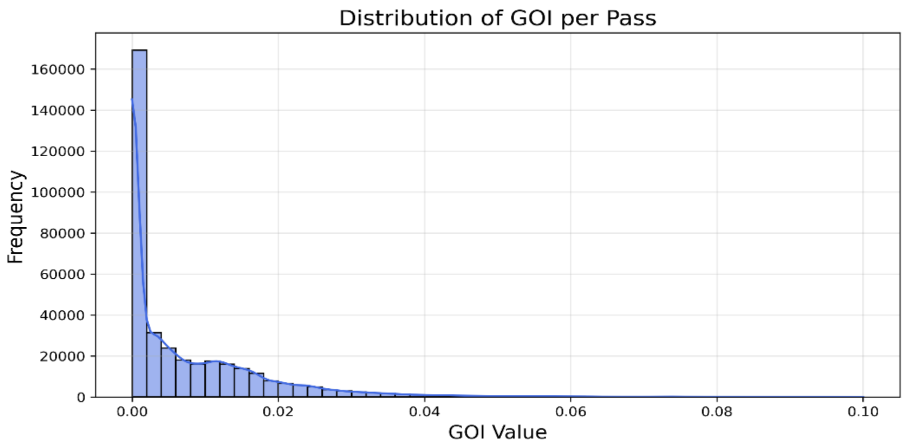

Figure 4. GOI distribution

In Table 4, the GOI values are very close to the mean, with a moderate right skew, suggesting that costly decision-making mistakes occur from time to time. The mean and median being close together means that the average quality of decisions is steady. The higher 75th and 95th percentiles indicate that some passes incur much greater opportunity loss than others. The highest GOI levels exhibit rare but crucial mistakes. Overall, the distribution shows that GOI can accurately identify both standard decision-making patterns and the important outlier occurrences that change the course of a match.

Table 4. GOI Summary Statistics

Statistic	Value
Mean	1.087
Median	1.143
75th Percentile	1.427
95th Percentile	1.779
Min	0.161
Max	3.222
Skewness	0.609

6.1.2 GOI Trend

Table 5. GOI by match phase

Match Phase	Mean GOI	Median GOI	75th Percentile	Num Events
0–70	0.0075	0.0028	0.0117	285879
70–90	0.0076	0.0029	0.0119	69962
90+	0.0087	0.0042	0.0135	9576

In Table 5, the GOI values are presented during the most important phases of matches. In the first 70 minutes, the GOI remain relatively consistent. During the 70–90-minute period, due to fatigue and pressure, the GOI average begins to increase. Injury time (90 minutes) has the highest GOI values. This supports the theory that decision quality weakens as fatigue sets in. Figure 5 provides a visual overview of the GOI as matches progress.

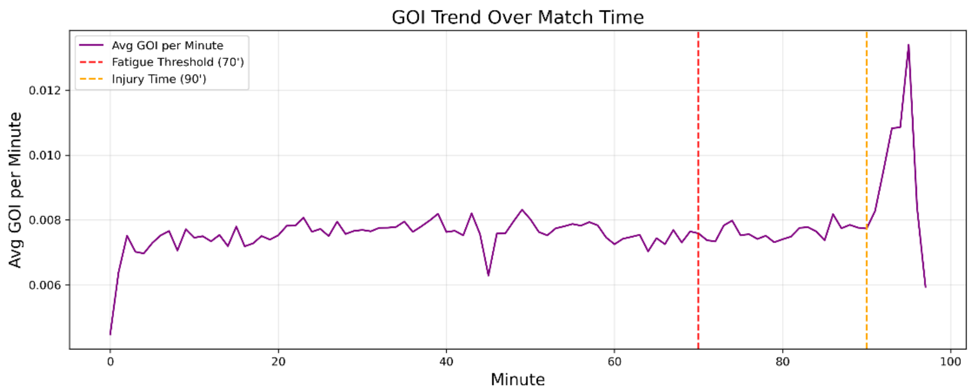

Figure 5. Trend over match time

6.1.3 Player evaluation

Figure 6 highlights the 20 weakest Barcelona players from a decision-making perspective; mostly, they are forwards or attacking players. The best GOI scores are players in a buildup role, playing more defensive roles, and under less pressure.

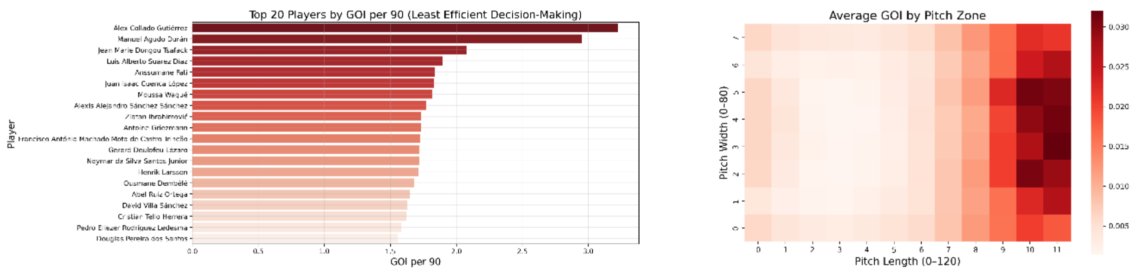

Figure 6. Player level evaluation of GOI

The heatmap supports this data, indicating the areas with the highest GOI rates. The attacking half with higher-risk passes to threaten the opposition. Some players have very high GOI scores, but this was due to only a small number of playing minutes, indicating that the minimum number of minutes is required for the success of the substitution system.

6.2 Formation Drift Index (FDI)

6.2.1 Behaviour across matches

From Figure 7, we can see stable drift during the first 30 minutes of the match. Between 55 and 70 minutes, which is usually when most substitutions are, there is a slight increase in drift. As expected, we can see a strong drift after 70 minutes, when fatigue and high pressure start to kick in.

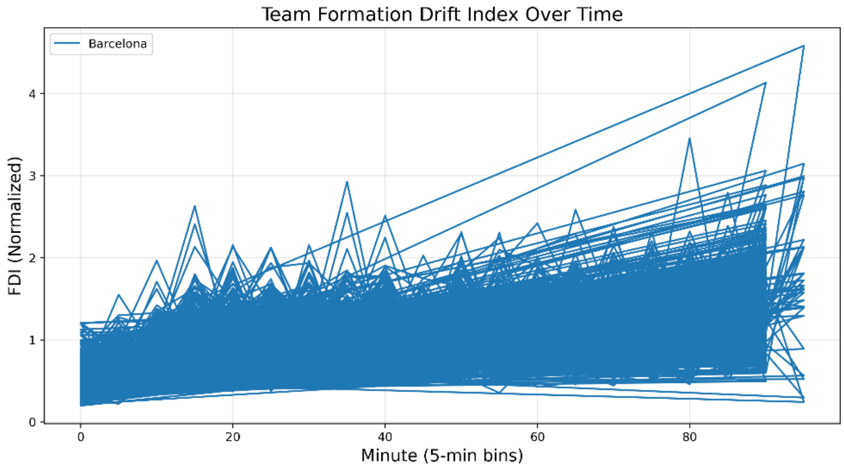

Figure 7. Team Formation Drift

From Table 6, the mean and median are close, indicating that most Barcelona players stay close to the baseline formation, confirming the known tactical aspects of Barcelona: discipline, ball possession and control in most of the spaces.

Table 6. FDI Distribution Summary Statistics

Statistic	Value
Mean	15.858
Median	15.317
75th Percentile	18.944
95th Percentile	23.118
Max	95.359

At the 75th and 95th percentiles, the upper ranges of drifts begin to change, especially at the 95th percentile, rising to much higher levels, indicating fatigue is setting in and the possibility of a breakdown in defensive pressure. The max is extremely high and points to outlier events, potentially due to the team losing structure during fast-paced or red-card situations.

6.2.2 Players positional analysis

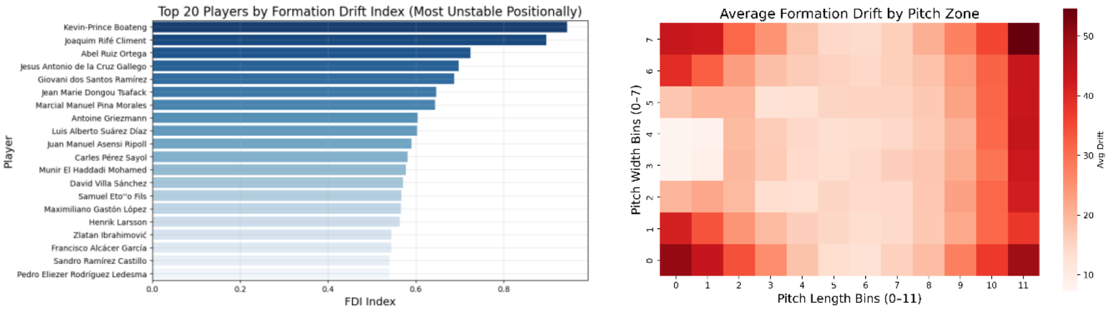

Figure 8. Player level evaluation of FDI

Figure 8 depicts the top 20 players with the highest drift index, along with a heatmap showing the area of the pitch where the most drifting occurs. This analysis showed that central defenders and pivot players, usually a low-hanging midfielder, display the lowest drift index as they are expected to anchor the formation. Left and right backs, along with wingers, exhibit high drift due to the attacking nature of their positions.

6.2.3 Overall summary

There is a strong correlation between FDI, loss of compactness, fatigue, and structural breakdown. This provides a strong indication that FDI can successfully identify drift patterns during matches and provide a good team-level measure.

6.3 High Pressure Expected Impact (HPEI)

6.3.1 HPEI Distribution

Figure 9 shows how well Barcelona players passed the ball under pressure. The x-axis, the average xT gain per pass, indicates a player's effective movement of a ball in a scoring area. The y-axis, the mean HPEI, is the expected impact adjusted for defensive pressure. The bubble's size reflects the number of passes and the colour of the quantity of actions taken under pressure.

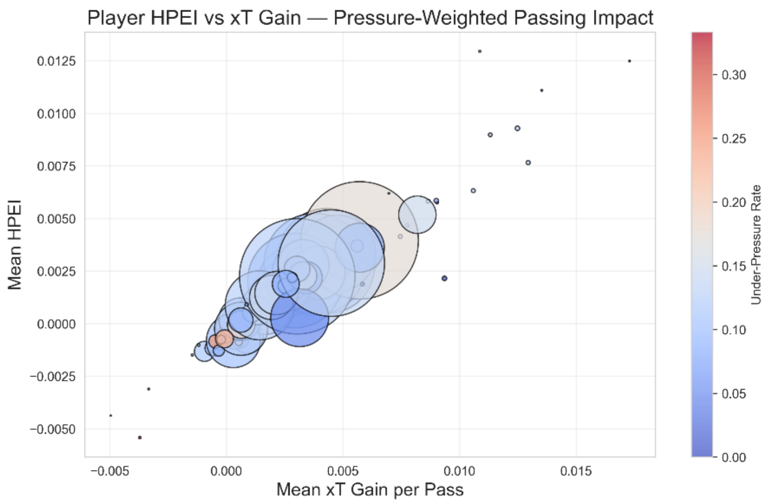

Figure 9. HPEI Distribution

Players in the top-right quadrant are core structural playmakers because they have both high progression and high pressure-resistance. Players in the bottom-right do well when there is not much pressure, but they do not do as well when there is. The top-left shows players who are safe but can be pressured, and the bottom-left shows players who do not contribute much overall and are good candidates for replacement. This visualisation puts performance in context by showing how consistently players contribute when faced with strong defence.

Correlation table 7 indicates a strong positive association between HPEI per 90 minutes played and mean xT gain, indicating that players who produce the most threat also have the greatest pressure-adjusted impact. HPEI is a good extension of xT because it accounts for pressure and the likelihood of a successful pass. Both HPEI and xT show negative associations with under-pressure rate, indicating that defensive pressure adversely affects offensive efficiency. This supports the theoretical hypothesis that pressure reduces decision quality and technical performance. In general, the table shows that HPEI accurately describes the relationship between creating threats and the pressure environment.

Table 7. HPEI Correlation Matrix

	HPEI per 90	Mean xT Gain	Under pressure
HPEI per 90	1.000	0.839	-0.257
Mean xT Gain	0.839	1.000	-0.252
Under pressure	-0.257	-0.252	1.000

6.3.2 Player level impact

Barcelona players under pressure had higher HPEI, and underperformers showed sharp drops in HPEI, indicating a consistent link between high HPEI and advanced playmaking roles. This is depicted in Figure 10, showing the top 20 players by HPEI and a heatmap indicating where the highest pressure was applied.

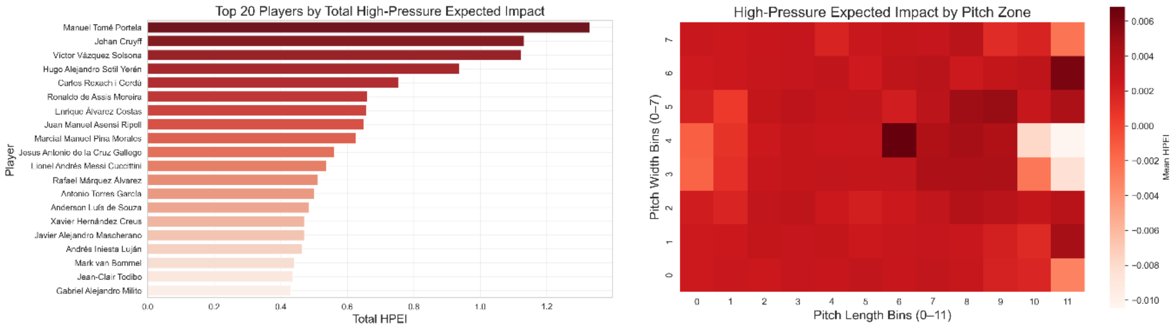

Figure 10. Player level impact for HPEI

6.3.3 Overall summary

There is a strong correlation between FDI, loss of compactness, fatigue, and structural breakdown, indicating that FDI can successfully identify drift patterns during matches and provide a good team-level measure.

Table 8. HPEI Summary Statistics

Statistic	Value
Mean	0.206
Median	0.175
75th Percentile	0.337
95th Percentile	0.652
Max	1.331
Under pressure rate	0.124

Table 8 summarises the High Pressure Expected Impact (HPEI) across all Barcelona players. The mean and median results showed that most players handle pressure well. There is a marked difference in the 75th and 95th percentiles, indicating the impact of high-pressure playmakers. The top 5% have an HPEI of more than 0.65, indicating how well they handle pressure. The maximum recorded HPEI highlights rare sequences of elite decision-making and high-impact progression. The mean under-pressure rate of only 12.4% confirms that Barcelona typically operates in low-pressure environments, making HPEI a sensitive indicator of players whose performance changes significantly under defensive pressure.

6.4 Substitution Recommendation

GOI, FDI, and HPEI make up the core layers of the substitution recommendation. These three-dimensional layers are transformed into a substitution layer to support real-time substitutions; when any on-field player meets the substitution criteria, it is flagged for substitution.

6.4.1 Substitution Distribution

Figure 11 clearly shows that most of the model's substitution recommendations fall within 10 minutes of the actual substitution, but that the model's substitution was indicated earlier than the actual substitution.

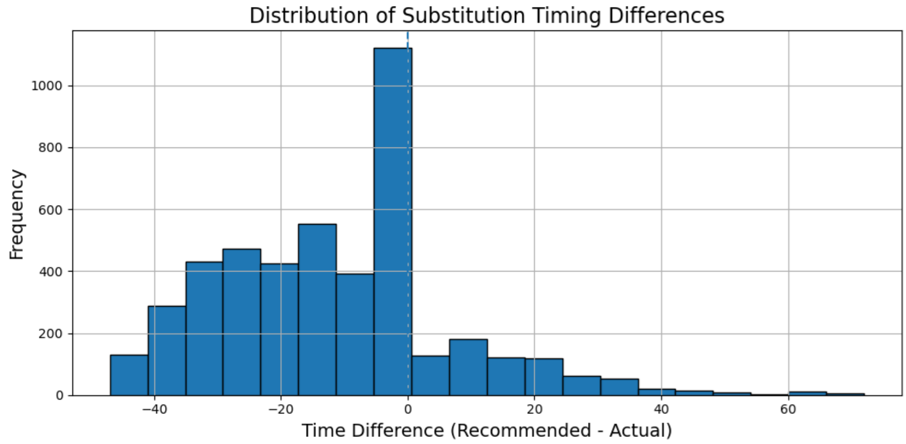

Figure 11. Substitution Distribution

Looking at Table 9, the mean time difference between this recommendation system and actual substitutions indicates that this system is proactive and identifies early signs of team and player performance deterioration. The player match rate is low, but this is to be expected as the system does not account for injuries, opponent behaviour or even squad rotation. System stability and operational integrity are clear due to the coverage of recommendations for every match.

Table 9. Substitution Metric

Metric	Value
Mean Time Difference	-11.163
Player Match Rate (%)	6.169
Coverage (%)	100.00

6.4.2 Actual vs recommended

Table 10 provides an overview of the accuracy of the actual substitutions and the recommended substitutions. The forwards show the lowest accuracy rate, which could be because forwards naturally exhibit high GOI volatility due to high-risk decision-making and large HPEI swings from pressing and counter-pressing. This makes them more likely to be flagged. Defenders are more often substituted due to injury and cards, as well as structural changes in the competition. This makes identifying defenders harder. Midfielders show the highest accuracy; this is because they are more critical to drift formation, ball retention (xT), and press resistance (HPEI), making their performance decline more visible.

Table 10. Actual vs Recommendation accuracy

Position Group	Total Recommendations	Correct Predictions	Accuracy (%)
DEF	419	36	8.592
FWD	3889	198	5.091
MID	231	46	19.913

6.5 Discussion

6.5.1 Alignment with Existing Literature

Part of this study examines decision-making under pressure, and reveals that the GOI peaks in injury time, aligning with findings that mental fatigue and stress decrease performance and increase missed opportunities (Jordet, 2009). The GOI offers an improvement over existing models by assessing the value lost at the micro-decision level, and its spatial clustering confirms its methodological consistency with threat valuation research. The Formation Drift Index (FDI) indicates tactical role detection using event data and shows instability phases from the 70th minute, aligning with prior research on formation disruption (Bialkowski *et al.*, 2014). The High Pressure Expected Impact (HPEI) successfully identifies press-resistant players by combining temporal weighting and pass-success probabilities, thus providing insights into players' technical reliability under pressure. These results are consistent with (Spearman's, 2018) research on pressure-adjusted action valuation.

Additionally, the study addresses the literature gap regarding real-time substitution systems by incorporating FDI, HPEI, and decision-making methodologies. Prior research done by (Pawlowski *et al.*, 2007; Wright *et al.*, 2011) focused on match timelines and scorelines, and that of (Baadi *et al.*, 2025) focused on machine learning methodologies to predict the impact of substitutions after the implementation. Still, none of these studies used the FDI HPEI and a real-time decision-making system for substitution. The system in this study addresses that gap.

6.5.2 Interpretation of Findings and Limitations

Interaction Between GOI, FDI, and HPEI

Multi-level convergence exists between GOI, FDI, and HPEI. GOI found micro-level player decision-making inefficiencies, FDI found structural organisation problems, and HPEI showed technical performance declined under pressure. These signals complemented each other. HPEI dropped when formation drift increased, lowering press resistance, and when FDI is high, GOI often increases, suggesting structural instability, making good decision-making tougher.

Interpretation of Low Player Overlap with Real Substitutions

The system, rather than copying human behaviour, instead is meant to find latent player performance risk, whose decline is not yet apparent to the eye. The evidence comparing real-world and model substitutions suggests that the model offers innovative, autonomous tactical insights, rather than merely reflecting traditional coaching practices. This difference is vital for an effective decision-support system, meant to support decision-making and not copy them.

Limitations

The recommendation system developed in this study has some limitations that prevent it from reaching its full potential. The lack of full GPS tracking keeps the formation drift index from fully understanding structure changes. Fatigue monitoring will make the recommendation system even more powerful, but this information is not available in the data. A lack of lineup data makes it harder to fully evaluate against actual substitutions, as only data for players who played during the match are available. Substitutes who did not come off the bench do not have any possession data. The system was applied only to Barcelona because they had the most complete data, making it difficult to run on other teams. GOI could be high if management tells players to make high-risk passes during high-pressure moments, and this will not be reflected in the data itself. The limitations of this study do not invalidate the system but only give potential future improvements.

6.5.3 Contribution of the Study

By developing a multi-layer performance indicator that combines formation changes (FDI), decision-making (GOI), and high-pressure situations (HPEI) into a single analytical framework, this study extends previous xT-based and action-value models by incorporating formation and mental pressure. This advances data analytics by offering a rule-based substitution recommendation system that does not rely on machine learning or on-the-go substitutions made by management, providing real-time tactical insight into player performance decline. Lastly, the study shows that event data, by itself, can be used to derive pressured performance and formation drift, thereby improving sport analytics. When taken as a complete set, these contributions move open-data football analytics from descriptive post-match analysis to prescriptive, tactical decision support during the game.

7 Conclusion and Future Work

This study tested whether an expected threat-driven system for Ghost Opportunity Index (GOI), Formation Drift Index (FDI), and High Pressure Expected Impact (HPEI) can be used to create a system to give the timing and selection of substitutions during high-pressure match phases, leading to the development and evaluation of a combined, multi-layer substitution recommendation system. The results showed that all three methods were effective: the GOI can detect when a player's decision-making starts to decline; the FDI can detect when there is a breakdown in formation; and the HPEI measures pressure-adjusted technical performance, with all three methods working very well together to generate realistic substitution timing and substitution recommendations.

Although missing lineup and match-state data limited validation against actual substitutions, the system demonstrated strong, consistent behaviour, suggesting it could also be used for early detection of need substitutions. Overall, the findings confirm that the expected threat-driven, multi-layer performance modelling can deliver a sound, interpretable, and real-time substitution decision-support system using open-source event data alone.

Although the proposed system shows a strong performance, there is still room for future work and improvements. The use of full GPS tracking could improve the analysis of formation drift by providing a clearer overview of structures to fine-tune the FDI. With the inclusion of the scoreline and fatigue monitoring, the HPEI could be much more accurate. Complete lineups could improve comparisons between actual and recommended substitutions. This system could also be improved by making better use of reinforcement learning techniques in future developments alone.

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