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Applying an Expected Pass Turnovers model to inform pressing strategies in professional football

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ABSTRACT

The aim of this study was to apply the Expected Pass Turnovers (xPT) model and demonstrate its practical applications within a practitioner setting. The model was implemented using event data and positional data from all 380 matches in the 2020/21 English Premier League season, comprising 256,433 passes in the final dataset. Players exhibiting lower pass retention ability, as quantified by xPT, can be identified as pressing targets for opposing teams and subsequently can be targeted through deliberate pressing strategies to regain possession. Furthermore, the defensive quality of players was evaluated using a complementary metric derived from xPT, termed Expected Pass Turnovers Forced (xPTF). As xPT quantifies the probability of turnovers for each pass based on contextual features, xPTF extends this by attributing these probabilities to the defending player applying pressure. Hence, the xPTF value was calculated for all passes made under pressure and attributed to the closest player executing the pressure action. Team-level xPTF performance correlated with Passes per Defensive Action (PPDA; $R = -0.52$, $p < 0.05$), supporting the metric's validity. Overall, the xPT model provides actionable insight into potential pressing targets, while xPTF serves as an evaluative tool for assessing individual and team pressing performance.

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KEYWORDS

Football metric; expected pass turnovers; performance analysis; football applications

1. Introduction

Performance analysis in football has evolved with the development of bespoke Key Performance Indicators (KPIs) to quantify specific aspects of play (Herold et al., 2021). Metrics such as expected goals evaluate chance creation (Lucey et al., 2014), expected threat assesses ball progression (Singh, 2019), and expected pass turnovers (xPT) evaluates the likelihood of losing possession of the ball through passing (Peters et al., 2024). A lot of current literature places a great emphasis on formulating attacking KPIs (Clemente et al., 2015; Liu et al., 2015; Lucey et al., 2014; Singh, 2019), with a dearth of research investigating KPIs evaluating good defensive performance (Forcher et al., 2022). This is surprising as impressive defensive performance relates to successful match

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outcomes (Lepschy et al., 2020) and the defensive phases of play: transition to defence and established defence (Hewitt et al., 2016) contribute to a large proportion of gameplay. In addition, owing to football's low scoring nature, there is a large importance placed on defensive performance to minimise shooting opportunities for opposition teams (Forcher et al., 2024).

Of the existing literature on defensive performance, some focused on different types and regions of ball recoveries (Almeida et al., 2014; Jamil et al., 2025; Santos et al., 2017; Sunjic et al., 2025; Yang et al., 2025). However, this literature focused on general team ball recovery trends as opposed to evaluating the impact of individual ball recovery and its relationship with applying pressure (or pressing behaviour). As positional data became more readily available, recent literature has investigated applying pressure as a defensive strategy to recover the ball. This defensive strategy is referred to as pressing and it occurs whereby players collectively exert pressure on the opponent with the ball, and the likely pass recipients, with the objective of winning the ball back, usually in the opponent's half (high press; Merckx et al., 2021). Low et al. (2021) analysed the contrasting defensive strategies: high-pressing and deep defending, by using a local positioning system to capture positions of all players in a trial match. Whilst the findings were limited due to the trial-based nature of the study, small sample size and the use of youth footballers, it was a seminal study in reporting the descriptive nuances of a high pressing defensive strategy.

In addition to trial-based analysis, there has been an effort to measure and attribute value to pressing behaviour (Robberechts, 2019). However, pressing is quite difficult to characterise quantitatively, as multiple players apply pressure to the ball and likely pass recipients when performing successful pressing behaviour. Existing data providers have attempted to measure individual ball pressure actions, by assessing if an opposition player has entered a certain radial distance from the ball carrier (Yam, 2018). Basic measures of these events include counts, and their calculated proportions (such as the proportion of pressure actions in the opposition half), to evaluate a team's performance (Lago-Penas & Dellal, 2010). However, the number of pressure actions from game to game may be skewed, owing to variation in opposition possession proportion. To overcome this, pressing proxies have been proposed. Passes per defensive action (PPDA; Trainor, 2014), is calculated by aggregating defensive actions (tackles, interceptions & foul events) in the opposition 60% of the pitch and dividing this total by the number of passes the opposition makes. The number of opposition passes is used to normalise the defensive actions made, as this has a significant correlation with possession time (Collet, 2013) and hence is a suitable proxy to measure opposition possession. A limitation of PPDA is that it evaluates pressing performance as a single value. Hence, PPDA's aggregated format obscures individual contributions and spatial patterns, limiting tactical insight.

In recent times, methods with greater sophistication have attempted to evaluate pressing performance. An XGBoost model (Robberechts, 2019) was built which values the risk-reward trade-off of pressing by estimating the probability of a team retrieving possession versus the probability of conceding a goal-scoring opportunity, both in the near future after pressing. However, event data alone is considered in this model, which may fail to capture an important component of pressing – the positions of teammates collectively performing the pressing action.

A sophisticated pressure metric that did consider positional data was created by Andrienko et al. (2017). The authors used various positional features such as: angle, distance and orientation of multiple players to calculate the pressure applied in a mathematical-based method. This pressure metric was adopted in further studies (Forcher et al., 2024; Herold et al., 2022; Merckx et al., 2021) and applied to different sports such as ice hockey (Radke et al., 2021). A further method incorporated this pressure model to analyse pass-risk reward (Goes et al., 2022). Although these methods are a viable way to quantify and measure pressure, there are gaps in a practitioner setting as to how these models are applied. For example, metrics that analyse player passing risk, such as xPT (Peters et al., 2024), can help identify opposition players termed as candidate pressing targets. These pressing targets are players that lose the ball more frequently relative to other players in the same position and can be targeted with an opposition pressing strategy to successfully regain possession.

A further application that has been underrepresented in the current literature is evaluating the ability of defensive players to retrieve possession, or successfully press. This can be achieved by attributing the xPT value for all passes that are made under pressure in the opposition 60% of the pitch (Trainor, 2014), to the player(s) performing the pressure action. The result is a defensive metric, named Expected Pass Turnovers Forced (xPTF). Hence, players with high Expected Pass Turnovers Forced (xPTF) values are associated with pressing in the correct areas of the pitch (high probability of winning the ball back) and may be representative of pressing teams with high pressing frequency. xPTF can also be considered on the collective level to assess the performance of team pressing. This may provide a more informative estimate of team pressing quality than existing pressing metrics such as PPDA, which may better approximate pressing volume as opposed to quality.

Overall, applications of the Expected Pass Turnovers (xPT) model (Peters et al., 2024) are presented in this paper (Figure 1). The overall aim was to convey the utility of the xPT model in a practitioner setting. To achieve this, the sub-aims were categorised as follows:

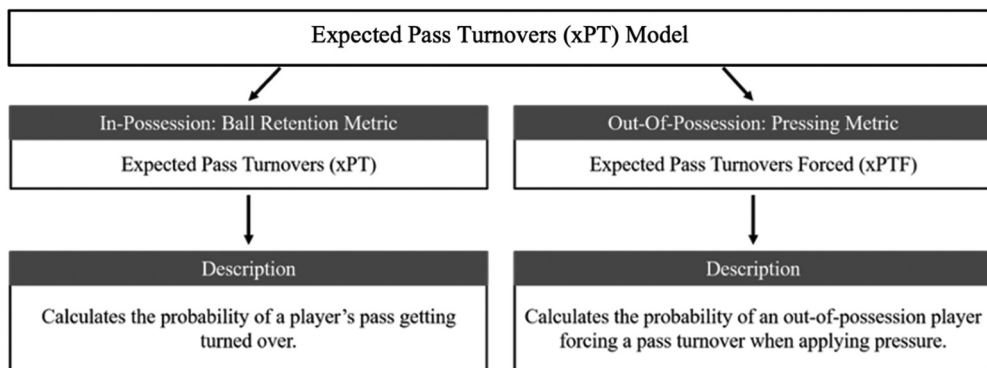


Figure 1. Flow diagram of the two metrics created using the Expected Pass Turnovers (xPT) model.

- (1) Examine players and pitch locations with elevated xPT values to identify potential pressing targets.
- (2) Analyse “high-risk” passes, as these may indicate opportunities when opponents are most vulnerable to pressure.
- (3) Quantify defensive players’ pressing performance using $xPTF$.
- (4) Compare team-level $xPTF$ performance with PPDA, recognising PPDA as a pressing volume proxy.
- (5) Provide a transparent and replicable methodology suitable for practitioners.

2. Methods

2.1. Positional data

Event and positional data from all 380 matches of the 2020/21 Premier League season were provided by *StatsBomb* (2022). The positional dataset included multiple rows per event freeze-frame and hence had to be reduced to a single row before appending onto the event data. Firstly, to standardise distances across different pitch sizes, X and Y coordinates were converted to metres by scaling them to the respective team’s stadium dimensions (Peters et al., 2024). Then, two positional feature sets were derived in accordance with Peters et al. (2024): (1) the presence of unmarked teammates in four directions relative to the ball carrier: left (-100° to -45°), right (45° to 100°), in front (-45° to 45°), and behind (remaining angles), and (2) the number of opposition players within three defined pressure radii.

2.1.1. Unmarked teammates

Minimum distances between each possession-team player and opposition players were calculated, and teammates located within 2 metres from an opponent were considered marked. Binary variables were then created for each direction, with TRUE indicating the presence of at least one unmarked player in that sector, resulting in four marked-teammate indicators.

2.1.2. Pressure radii

Pressure radii were computed to reflect the varying defensive intensity depending on proximity to the opposition goal. For possession events occurring more than 24 metres from goal, the base pressure radius was fixed at 4.5 metres. For events within 24 metres, the radius was scaled using the equation: $\text{distance_to_goal} \times 0.15 + 0.85$, generating a pressure gradient that increases closer to goal (Equation 1; Yam, 2018). Three concentric pressure radii were then defined as: 1) half, 2) equal to, and 3) twice this base radius. The number of opposition players within each radius was counted, producing three pressure variables.

$$d = DFG = \text{distance from goal(in meters)}$$

$$PR(d) = \text{pressure radius(in meters)}$$

$$PR(d) = \left\{ \begin{array}{l} 0.15d + 0.85, \text{ if } d \leq 24 \\ 4.5, \text{ if } d > 24 \end{array} \right\}$$

Equation 1. Dynamic pressure radius calculation based on distance to goal.

Hence, the final positional dataset included the following variables of interest: event ID, four binary unmarked-teammate variables and three pressure-radii variables. This positional dataset was then left joined to the event dataset, based on the event ID.

2.2. Event combined with positional data

The combined dataset was filtered to contain exclusively pass events, by using the same exclusion criteria as Peters et al. (2024). Passes were excluded if their outcome was not categorised as successful, unsuccessful, or out of play; if they represented the initial pass from set-piece situations (e.g. goal kicks, corner kicks, free kicks, or kick-offs); if they were classified as crosses; or if they were played by goalkeepers (all categorisations were provided by the data provider). Initial passes from set pieces were excluded because they are typically made under no defensive pressure and are not representative of general, free-flowing match situations. However, subsequent passes occurring within the same pattern of play, as determined by the data provider, were retained for analysis. Crosses were excluded because they target high-threat areas with direct goal-scoring potential (Yamada & Hayashi, 2015) rather than being aimed directly at a teammate. As such, they tend to have a lower likelihood of completion and are not representative of standard passing behaviour. Passes by goalkeepers were removed as the KPI under investigation focuses exclusively on the performance of outfield players.

2.3. Model overview

The same logistic mixed effects model and event/positional variables as developed by Peters et al. (2024) were applied to the combined event and positional dataset. To account for the non-independence of each pass action, random effects were included in the model using the random intercepts method. Different player abilities, playing positions and match conditions lead to variation in pass completion performance and hence the variables *player id*, *playing position* & *match id* respectively were modelled as random effects in a cross-classified multilevel design. Playing position was categorised as per the data provider: Centre Back (CB), Full-Back (FB), Wing-Back (WB), Defensive Midfield (DM), Centre Midfield (CM), Attacking Midfield (AM), Winger (WG) & Striker (ST). The outcome was a value that attributed the probability of getting turned over (or xPT value) for all 256,433 passes analysed.

2.4. Performance indicators

Relating to the initial aims, a series of performance indicators were created:

- (1) Identifying Pressing Targets: Player xPT values were calculated as averages per 100 passes to provide practitioner-friendly coaching insights and enable position-specific comparisons. Median and upper quartile benchmarks were established

per position to identify potential pressing targets (values exceeding upper quartile). Team-level xPT averages were then plotted spatially across the defensive 60% to visualise zones of heightened turnover vulnerability.

- (2) **High-Risk Passes:** High-risk passes were defined as those with xPT values more than 2 standard deviations above the mean. Only high-risk passes occurring within the defensive 60% of the pitch were included in analysis, as this reflects the zone typically associated by pressing behaviour (Merckx et al., 2021; Trainor, 2014). Pass start and end coordinates were clustered using K-Means (NbClust, Charrad et al., 2014) to identify spatial patterns of vulnerability. Both start and end locations were included as features in a single cluster analysis.
- (3) **Players Forcing Turnovers:** Expected Pass Turnovers Forced (xPTF) was estimated by assigning the xPT value of each pressured pass, in the opposition's 60% of the pitch, to the nearest opposition player applying the pressure (Equation 2), providing a practical approximation of pressing influence. A pressure action was recorded whenever a defender was within a defined radius (Equation 1) of the ball carrier at the time of pass execution. Player xPTF performance was computed as actual turnovers forced minus expected turnovers forced, per 100 opposition passes pressured by that player.
- (4) **Team-Level Pressing:** Team-level xPTF was derived by aggregating individual xPTF contributions and calculating the average xPTF per 100 opposition passes. This was compared with PPDA using Spearman correlation, recognising PPDA as a proxy of pressing volume rather than pressing quality.

$n = \text{total number of pressured passes} \in \text{the opposition 60\% of the pitch}$

$d_i = \text{nearest defender to pass } i$

$$xPTF_{player} = \sum_{i=1}^n xPT_i x1(player = d_i)$$

Equation 2. Calculation of Expected Pass Turnovers Forced (xPTF) for individual players.

2.5. Statistical analysis

Descriptive statistics were calculated for all variables (Supplementary Table S1). Random effects were summarised to examine variability across players, positions, and matches (Table 1). Correlations were computed using Spearman's rank correlation. Analyses were conducted in R with packages lme4, NbClust, and ggplot2. The optimal number of clusters was determined using the NbClust package (Charrad et al., 2014), which

Table 1. Summary of random effects variables.

Factor	Variation (σ^2)	Notes
Player	0.08	Greatest variation in determining pass-turnover probability
Playing position	0.03	Lower variation
Match	0.02	Lowest variation

computes 30 validation indices and applies a majority voting rule to recommend the best clustering solution. K-means clustering was performed with Euclidean distance, testing cluster solutions ranging from $k = 2$ to $k = 10$. The cluster number receiving the most votes across all indices was selected as optimal. The R code to apply the model to sample data and generate the plots in this study is publicly available on GitHub at: <https://github.com/andypetes94/ExpectedPassTurnovers/>

3. Results

3.1. Identifying potential pressing targets

Figure 2 illustrates player *Expected Pass Turnovers* (xPT) per 100 passes for an anonymised team. As pressing primarily occurs in the opposition half, defensive players are typically considered potential pressing targets. Accordingly, full-backs (FB) and centre-backs (CB) with xPT values above the upper quartile (red box) represent potential pressing candidates. Within the anonymised team, the full-back *Player_4620* and centre-back *Player_3628* fall within this zone and thus exemplify players who may be considered pressing candidates based on the analysis.

3.2. Identifying spatially where teams are vulnerable to pressing

Figure 3 illustrates team-level average *Expected Pass Turnovers* (xPT) across the defensive 60% of the pitch, divided into a 2×3 spatial grid. The visualisation presents each team's xPT values relative to grid-specific percentiles, where green cells indicate zones of

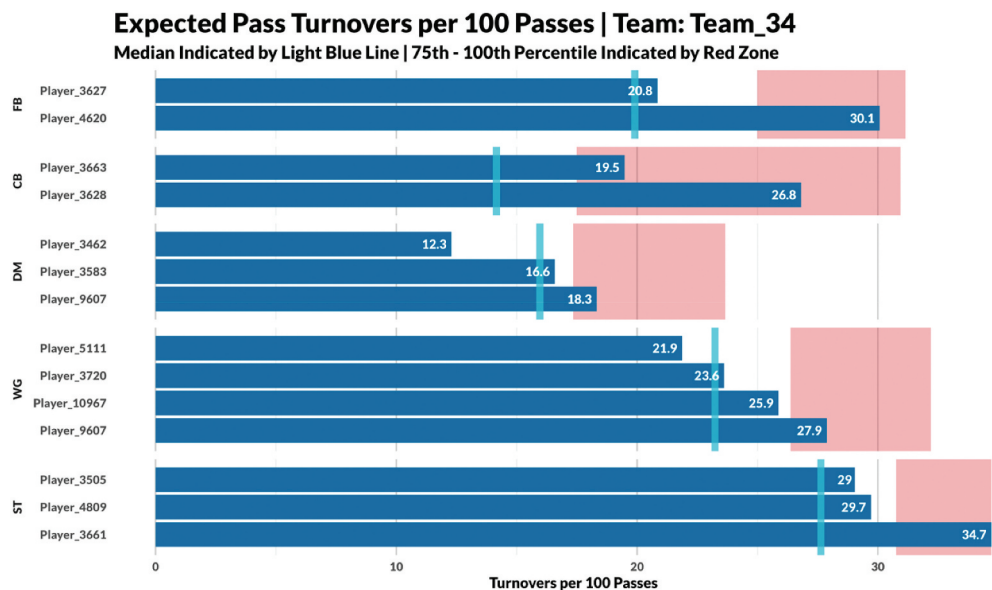


Figure 2. xPT of individual players from an anonymised team. Raw values are normalised per 100 passes played. The y-axis displays individual players that are grouped by position, starting from defensive positions to attacking positions.

Team Average Expected Pass Turnovers (xPT) Relative to Grid Percentiles

Green = Positive (Low Turnover) | Red = Negative (High Turnover) | Yellow = Neutral

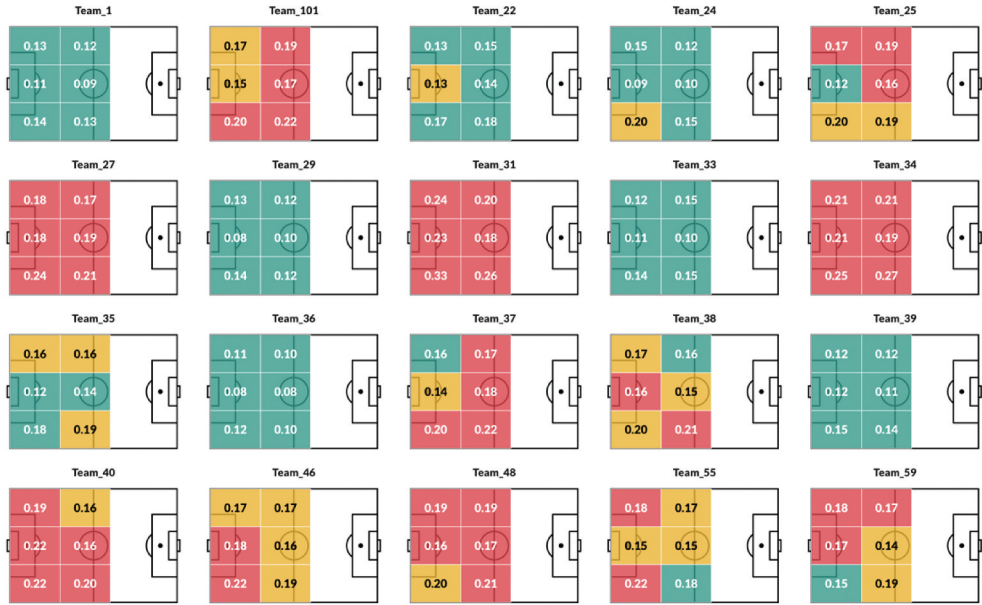


Figure 3. Team average Expected Pass Turnovers (xPT) relative to grid percentiles.

relatively low turnover probability (positive performance), red cells denote high turnover probability (negative performance), and yellow represents neutral values. Across teams, clear spatial heterogeneity is evident: several teams (e.g. Team_1, Team_29, Team_33, Team_39) exhibit consistently low xPT values across most defensive zones, suggesting stable ball retention in defensive areas. In contrast, others (e.g. Team_27, Team_31, Team_34) display elevated xPT values throughout, particularly in the central and right defensive thirds, indicating higher vulnerability to losing possession.

Values represent the mean probability of losing possession via passing actions within each grid cell of the defensive 60% of the pitch. Green = positive (low turnover), red = negative (high turnover), yellow = neutral. Each mini pitch corresponds to one team, illustrating spatial variation in ball retention risk across defensive areas.

3.3. Identifying teams' high-risk passes

K-Means clustering (6 clusters, *NbClust*) identified common high-risk pass start locations from an anonymised team (Figure 4). As is evident in clusters 1 and 6, this team plays many risky passes from defensive positions on their right side. Hence, this information may serve a two-fold purpose: 1) a team can investigate these passes in detail and explore the pressing shapes and structures that enabled these high probability turnover situations; 2) this information can also be used to target specific areas of the pitch or players in possession that may be particularly vulnerable to pressure from this opposition. This information can help prepare specific pressing behaviours when playing this opposition team in the future.

High-Risk Pass Clusters for Team_34

Total High-Risk Passes Analysed: 55 | Circles Indicate Pass End Locations

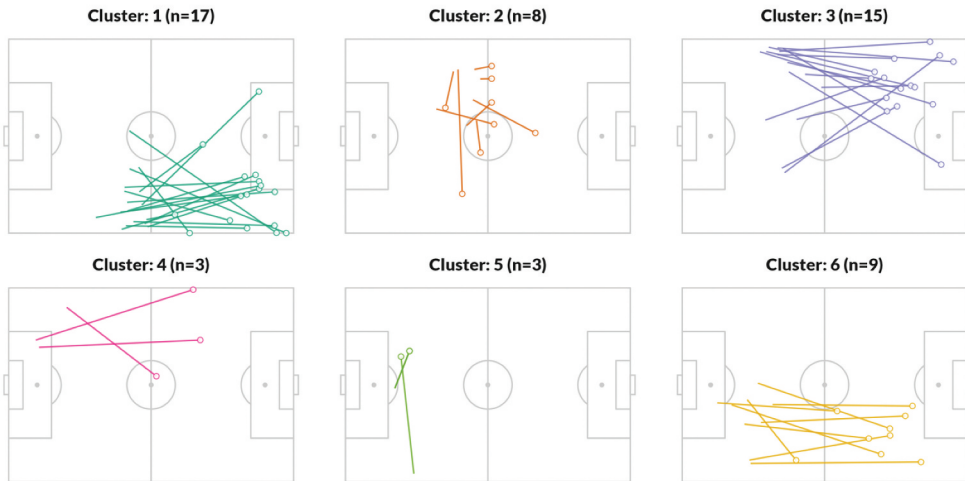


Figure 4. K-means clustering of high-risk pass locations ($xPT > 2$ standard deviations above the mean in defensive 60% of pitch) from an anonymised team. Pass origin is indicated by line end and pass destination is indicated by circle. Clusters 1 and 6 highlight a right-side dominance of risky passes for this anonymised team.

3.4. Identifying players that force turnovers

Figure 5 presents the top 20 players ranked by expected pass turnovers forced ($xPTF$). In the figure, the blue dots indicate normalised $xPTF$ values (per 100 passes played), while red dots positioned to the right of these values represent positive performance; conversely, red dots to the left indicate negative performance. Variation in these performance metrics may reflect individual ability, tactical context, or both. Players who generate a higher number of turnovers than expected may be associated with effective pressing actions, or may benefit from a well-defined team pressing structure that enables repeated ball recoveries. Conversely, players with lower-than-expected turnovers are highlighted by negative $xPTF$ values, reflecting comparatively lower effectiveness in retrieving possession within this framework.

3.5. Identifying teams that force turnovers

Teams that engaged in high pressing volume (low PPDA) tended to create more high probability turnover scenarios (high $xPTF$ per 100 opposition passes), as indicated by the significant correlation (Figure 6; Spearman $R = -0.52$; p -value < 0.05). An outlier to this correlation is Leeds United, which may indicate a mismatch between pressing volume and pressing effectiveness. Further outliers include Crystal Palace and West Ham United, who achieved similar pressing volume (PPDA value) yet occupy different ends of the pressing quality spectrum ($xPTF$ per 100 passes).

Connected Dot Plot: xPTF vs Turnovers Forced

Blue = xPTF, Red = Turnovers Forced

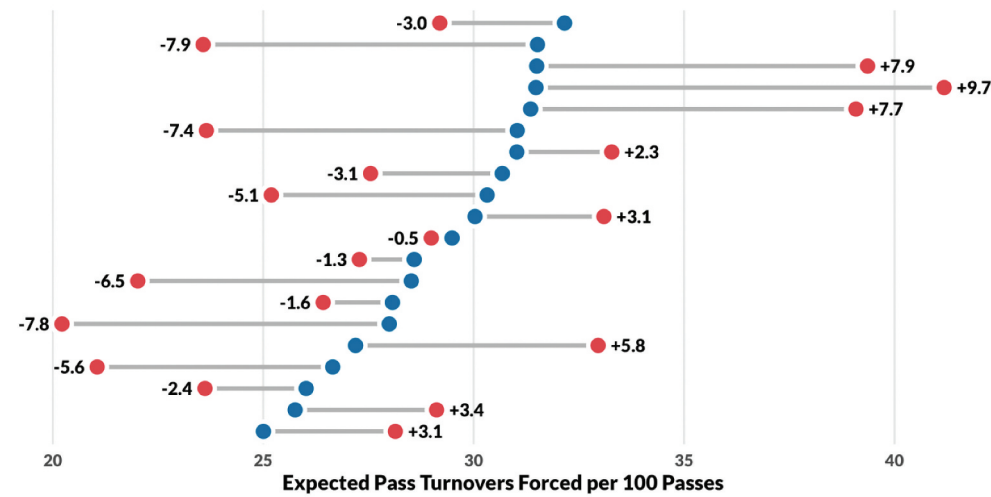


Figure 5. Top 20 players by xPTF value per 100 passes (blue circles). These values were compared with actual turnovers forced (red circles) across the season. Players' xPTF performance displayed by numbers, with a positive performance indicating forcing a turnover above expectation.

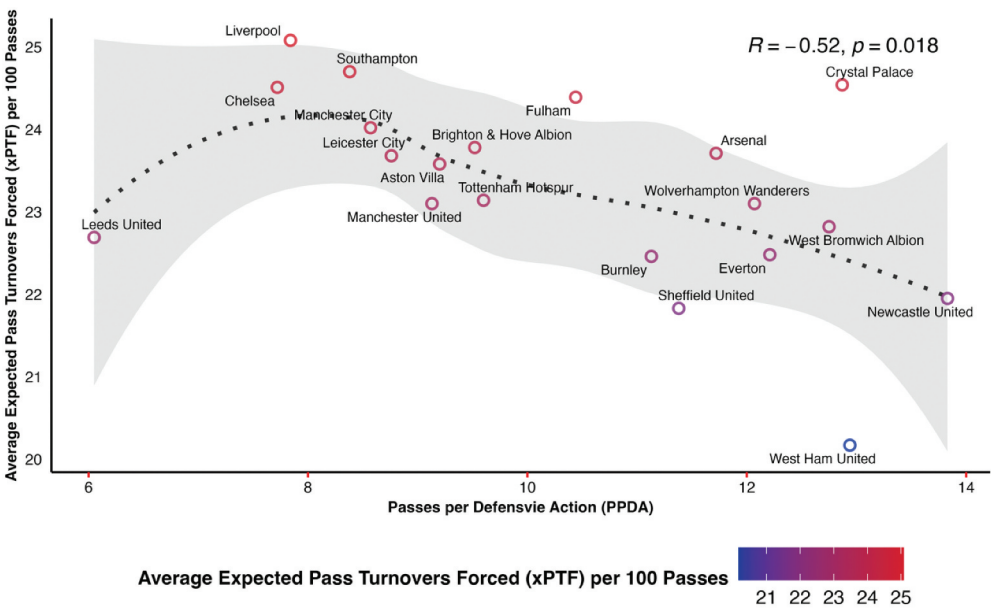


Figure 6. Team xPTF per 100 opposition passes in the opposition 60% of the pitch vs. PPDA. Spearman correlation $R = -0.52$ ($p < 0.05$) supports xPTF.

4. Discussion

4.1. Overall discussion

The aim of this study was to apply the Expected Pass Turnovers (xPT) model and examine its practical applications. Overall, xPT provides a more informative and context-sensitive measure of passing performance than traditional pass completion rate, which is simply the fraction of successful passes over all attempted passes. Unlike this conventional metric, xPT incorporates contextual variation by accounting for player identity, positional group, and match-specific conditions through random effects in the model. Consequently, analysing league-wide player xPT enables identification of players who are more likely to lose possession through passing actions. Such players can be considered potential pressing targets, informing opposition pressing strategies aimed at efficient ball recovery. Although previous approaches have explored aspects of passing decision-making (Goes et al., 2022; Power et al., 2017), quantified pressing (Andrienko et al., 2017), and modelled spatial pressing behaviour (Bojinov & Born, 2016), to our knowledge, no previous research has directly applied passing-based models to identify pressing targets.

Beyond individual analysis, team-level xPT values can be examined across a season to identify situations and pitch regions in which teams are most likely to lose possession. Figure 3 illustrates how xPT was mapped spatially across the defensive 60% of the pitch, divided into a 2×3 grid, to visualise areas of elevated turnover risk. Teams exhibiting consistently high xPT values in defensive zones may be more vulnerable during early build-up phases, while those maintaining low xPT values across defensive zones demonstrate more stability in possession retention. This spatial representation enables practitioners to pinpoint specific sub-regions associated with high-risk passing and to replicate or counter these tendencies in tactical preparation. For performance analysts, such spatial xPT maps offer two key insights: (1) identification of players or zones associated with frequent possession loss, and (2) recognition of spatial patterns that can inform the design of pre-match pressing structures to exploit opponent weaknesses.

It is also possible to analyse defensive players' pressing performance with xPTF. Although previous methods have looked to model the value of pressing (Robberechts, 2019), the implementation of positional features with xPTF may lend additional situational context. A high individual xPTF value indicates that a player is frequently involved in pressing actions in advantageous areas to regain possession. Hence, a player with a positive xPTF performance could be associated with more effective pressing, or part of a successful team pressing strategy. Teams strategically direct pressing behaviour towards wide areas (Jamil, 2019; Jamil et al., 2025; Peters et al., 2025a), as these regions offer tactical advantages due to spatial constraints imposed by the touchline. Therefore, individual xPTF is an additional layer of information when evaluating players (particularly wide players) for recruitment processes and can be leveraged in data-driven approaches to classify different player pressing roles (Peters et al., 2025b).

When team xPTF performance is compared to PPDA (Trainor, 2014), there is a significant correlation (Figure 5; Spearman $R = -0.52$; p -value < 0.05). This provides initial support for xPTF, as it correlates with an industry standard pressing proxy. However, the utility of xPTF may be greater, as it may better approximate the quality of pressing rather than the volume of pressing, which PPDA derives. This may explain

why a team like Leeds United carried out a large volume of pressing (low PPDA) but did not repeatedly create high probability scenarios of possession retrieval (low xPTF per 100 passes; Figure 5). However, PPDA should be interpreted as a proxy for pressing volume rather than a direct measure of pressing quality, so stronger validation of xPTF would require examination of direct defensive outcomes such as successful ball recoveries following pressure actions.

Recent studies have employed Voronoi diagrams and pitch control models to analyse match contexts and reveal team interactions across all players (Fernandez & Bornn, 2018; Gonçalves et al., 2022; Spearman, 2018). These methods use player tracking data to quantify spatial dominance and control probabilities across the pitch. While these approaches provide comprehensive spatial coverage and capture the dynamic interactions of all 22 players, xPT and xPTF offer complementary advantages: (1) probabilistic quantification of turnover risk rather than descriptive spatial coverage, (2) direct attribution to individual players for actionable recruitment and tactical decisions, and (3) integration of both positional and event-level features. Future work could integrate Voronoi-based spatial control (Spearman, 2018) or space generation metrics (Fernandez & Bornn, 2018) with xPT to create a unified framework capturing both space occupation and turnover probability.

4.2. Limitations and future work

This study was conducted using event and positional data from the 2020/21 Premier League season. This was an unprecedented season, owing to disruptions caused by the COVID-19 pandemic and, most notably, the absence of spectators at matches. To ensure reproducibility and generalisability, future research should replicate this analysis using data from a non-disrupted season.

A limitation of the xPTF metric is that it attributes value solely to the player applying direct pressure to the ball. However, pressing is inherently a collective action in which multiple players contribute by constraining passing options and applying pressure to likely pass recipients (Merckx et al., 2021). Future studies could therefore extend the model by incorporating pressure calculations, such as those in Andrienko et al. (2017), for all potential pass recipients to examine how defenders' application or relief of pressure influences xPT values. A simpler alternative would be to apply the xPTF value of the ball-pressing player to all defenders applying pressure to an opponent within a defined spatial radius of the ball carrier. Nonetheless, given the coordinated and dynamic nature of pressing, isolating the relative contribution of each player remains a methodological challenge.

An additional limitation of this study is the exclusion of goalkeeper passes. While this exclusion allowed the study to focus on outfield player performance, it also means that an important component of modern build-up play was not captured. In contemporary football, goalkeepers are increasingly involved in possession sequences and are often used to trigger or bypass pressing structures, particularly in the early phases of possession. As a result, excluding goalkeeper actions may underestimate the full scope of pressing dynamics and turnover risk, especially in teams that rely heavily on goalkeeper involvement in build-up. Future research should therefore incorporate goalkeeper passes to provide a more complete assessment of team-level pressing behaviour and early-possession turnover risk.

Overall, these extensions would build directly on the current xPT and xPTF framework – augmenting its scope to capture goalkeeper involvement and collective pressing dynamics without undermining its core structure or established validity.

5. Conclusion

This study examined the applications of the Expected Pass Turnovers (xPT) and Expected Pass Turnovers Forced (xPTF) metrics using data from the 2020/21 English Premier League season. The xPT metric enables practitioner performance analysts to identify players who frequently lose possession through passing actions – termed as potential “pressing targets” – who may be strategically targeted in pre-match pressing plans. Additionally, xPTF facilitates the evaluation of individual pressing performance and may be extended to the team-level, offering insights into pressing performance. The validity of the xPTF metric was supported by a significant correlation with the established pressing proxy PPDA ($R = -0.52$; $p < 0.05$), providing initial support for the metric. Accordingly, xPTF should be interpreted as an applied proxy for pressing effectiveness rather than a standalone measure of press quality. Importantly, the implementation of the xPT model has been made fully reproducible through an open-source GitHub repository, enabling practitioner analysts to replicate the analyses and integrate the tool into applied performance workflows.

Future research could expand upon this framework by attributing xPTF values not only to the player applying pressure to the ball carrier but also to teammates simultaneously pressuring potential pass recipients. Such an extension would more accurately reflect the collective nature of pressing actions within team defensive structures.

Author contributions

CRedit: **Andrew Peters:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing; **Nimai Parmar:** Writing – review & editing; **Michael Davies:** Writing – review & editing; **Nic James:** Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

All code used in this study, including model implementation, cross-validation procedures, and plotting functions, is available on GitHub at: <https://github.com/andypetes94/ExpectedPassTurnovers>. This repository enables full reproducibility of the analysis presented in this paper and provides a framework for applying and extending the Expected Pass Turnovers (xPT) model to other datasets or competitions.

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