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**Coach-Rated Importance of Technical Performance Metrics
Across Playing Positions in Football: Introducing the Game
Performance Index (GPI)**

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Abstract

Introduction: Football is a dynamic and complex sport in which player impact is not always adequately captured by traditional performance statistics. While existing research has demonstrated the value of combining expert judgement with statistical methods, limited attention has been given to how coaches themselves prioritise technical skills across different playing positions. This study addresses this gap by examining coach-rated importance of technical actions by position and introducing the Game Performance Index (GPI) as a conceptual position-specific framework for structuring these evaluations.

Methods: Seven experienced coaches and analysts from Rangers Football Club participated during the 2023/24 season. Participants rated the importance of positive and negative technical skills (e.g., successful dribbles, unsuccessful progressive passes, aerial duels won) across six outfield positions (centre back, full back, defensive midfielder, attacking midfielder, winger, and centre forward) using a five-point Likert scale. The analysis focused on the Professional Development Phase (PDP), incorporating match data from 23 players across 30 fixtures. Descriptive statistics were used to assess agreement patterns, while regression modelling and analysis of variance examined differences in importance ratings by skill type and participant. Participant deviation analysis was used to explore individual differences in rating behaviour.

Results: Clear positional patterns emerged in how technical actions were valued, alongside notable overlap across roles. Defensive actions such as aerial and defensive duels were prioritised for centre backs and defensive midfielders but were also rated as relevant for forwards and wingers involved in pressing and defensive transitions. Attacking actions including chance creation, dribbling, and progressive passing were highly valued for attacking roles and remained important for deeper positions such as full backs and defensive midfielders, reflecting their role in build-up play. Differences in importance ratings were driven primarily by individual coaching tendencies rather than systematic differences between skill types. These findings illustrate that coach evaluations are shaped by positional demands and individual emphasis rather than a single uniform weighting structure.

Keywords: Football; Performance Analysis; Technical Skills; Coach Perceptions; Position-Specific Evaluation

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1.0 Introduction

Football's dynamic and multifaceted nature presents valuable opportunities for applying a range of analytical approaches to better understand player performance and the technical requirements of different positions. The genuine impact of a player on a particular match is not always fully reflected by simple statistics such as the quantity of shots, passes, or tackles (Escalera et al., 2019). Analysing data gathered from every player is crucial because it enables practitioners (coaches, performance analysts, etc.) to rate performance, identify which technical-tactical actions (such as dribbling, timing of tackles and interceptions, and lack of positioning to intercept the ball) require improvement. This process may inform the design of training sessions that support player development (Memmert, 2017).

Social networks have been utilised in numerous studies to evaluate individual performance (Grund, 2012). This approach applies concepts from other fields such as graph theory (Prathik, 2016) to determine which players in a football team are the most important, based on a set of predetermined metrics (Malta, 2014). While some studies have used the term “*influential player*” to describe those who affect match outcomes more than others (Clemente et al., 2015), others have described “*key players*” as individuals who dominate play and significantly impact team cohesion and tempo (Bargi, 2015).

Advances in technology have further transformed performance analysis. Carling et al., (2008) and Goto et al., (2015) demonstrated the value of systems that record and process player profiling data in line with team plans. Match analysis provides important insights into interactions between players, tactical effectiveness, and physical demands, with motion analysis now central to player and team development. Building on these advancements, Pereira et al., (2019) introduced the Golden Index (GI), a formula that quantifies individual and collective attacking contributions, while Ferreira et al., (2021) created the Defensive Golden Index (DGI), a weighted system for ranking defensive contributions. Both models highlight the potential of structured, statistically informed indices for capturing individual and collective performance.

The literature, however, falls short in evaluating player performance by position. This is a notable limitation, as the technical skills required vary substantially between playing positions and even within the same positional units (e.g., defence, midfield, attack).

Defenders, for example, typically rely on tackling, positioning, and aerial ability to prevent goals, while midfielders require vision and passing accuracy to link play and control tempo. Attackers, in contrast, depend more heavily on dribbling and finishing to create and convert scoring opportunities.

Position-specific performance analysis enhances tactical understanding by illustrating how effectively players fulfil their strategic roles within a team. For instance, full backs may be evaluated on their ability to contribute in both defensive and attacking phases, whereas central defenders are more commonly assessed on aerial duels and organisational qualities (Sarmiento, 2014). Such role-based breakdowns enable coaches to assess tactical effectiveness, adjust player deployment, and identify areas for improvement.

For younger players, the use of accurate position-specific data is particularly valuable in supporting long-term development, as it highlights areas requiring targeted training and promotes focused progression. Understanding role-specific skills at the individual level, and their contribution to overall team performance, can further support decision-making in team selection, scouting, and the design of tailored development plans (Robertson, 2016). Position-specific tracking therefore enables customised evaluation measures that better reflect the technical demands of each role (Aquino, 2020).

Coach evaluations remain a cornerstone of football assessment, yet they are inherently subjective and shaped by individual philosophies, experiences, and contexts (Mills et al., 2012; Larkin & O'Connor, 2017). Perceptions of importance can vary even within positional groups (Sarmiento et al., 2014), meaning that position or skill type cannot be analysed in isolation. Integrating coach perspectives with position-specific technical demands may offer a holistic, context-sensitive, and practically relevant approach (Carling et al., 2013; Bradley et al., 2013). For example, a central defender's aerial ability may be prioritised differently depending on tactical emphasis, while chance creation in midfield may hold greater or lesser value depending on style of play.

Alongside coach input, commercial platforms also play a major role in player assessment. Opta, one of the most widely used providers, collects over 3,000 match events - including passes, shots, and tackles - through automated tracking, manual coding, and video verification. Many platforms such as WhoScored, FlashScore, and FotMob rely on Opta data to generate ratings. However, algorithms used by these systems are proprietary and lack transparency. For example, Opta's model 'Opta Points' incorporates 18 variables, yet details

of the weighting process remain undisclosed. Moreover, such models rarely consider contextual factors like tactics or roles and rarely cover academy-level matches, where developmental progress is most critical. This reinforces the importance of understanding how coaches themselves value technical skills across positions - an area this study explores in depth. Monitoring player performance in academy games is particularly valuable for supporting individualised training and fair player assessment. Layton (2023) showed that performance tracking helps coaches design tailored training, reduce bias in evaluations, and manage workloads to prevent injury. It also assists in talent identification, strategic planning, athlete motivation, and peer benchmarking. These benefits underline the role of data-driven approaches in supporting young athlete development and ensuring impartial, informed decisions in academies.

1.1 Study Aims & Objectives

The present study has two primary aims, 1) to explore which technical performance metrics football coaches consider most important for each playing position, and 2) to examine how coach perceptions differ from one another, and how they align or contrast with existing literature. As part of this process, a new model - the Game Performance Index (GPI) - was developed to visualise coach-rated variable importance across positions. While not a validated tool, the GPI is presented as a conceptual framework to structure comparisons and provide a basis for future refinement in player evaluation.

2.0 Literature Review

Having established the rationale and aims of the study, the next section reviews existing research to contextualise its focus. The literature review examines how technical performance has been measured and interpreted within football, with emphasis on position-specific requirements and the influence of coach perceptions. Understanding these foundations is important for framing how the current study explores coaches' opinions on the relative importance of technical actions across positions, and why both positional role and skill type must be considered together when evaluating player performance.

2.1 Conventional & Novel Metrics

The evolving nature of football as a sport hinders the ability of conventional metrics (e.g., quantity of passes or shots) to fully capture player performance because they are unable to express a player's total impact on the game. While such statistics offer a basic overview of player involvement, they fail to account for the quality, context, and tactical relevance of each action (Rein & Memmert, 2016). For example, a high number of passes does not indicate whether those passes advanced play, broke opposition lines, or merely maintained possession in non-threatening areas. Similarly, shot count alone does not distinguish between long-range efforts under pressure and high-quality chances inside the opposing box. As a result, these surface-level metrics often overlook the nuances that define effective performance. These limitations highlight the need for more sophisticated performance indicators—ones that incorporate positional responsibilities, game context, and the relative importance of different actions across playing positions (Sarmento, 2018).

Much research has developed measures such as betweenness centrality and closeness centrality, drawn from social network analysis (SNA), to provide a more comprehensive assessment of individual player contributions (Clemente et al., 2015). Betweenness centrality measures how often a player acts as a bridge in passing sequences—essentially identifying players who connect different areas of the pitch or serve as vital links in ball progression (Gonçalves et al., 2017). For instance, a central midfielder who consistently receives the ball from defenders and distributes it to attacking players may have high betweenness. Closeness centrality, on the other hand, captures how quickly a player can interact with all other players in the network, highlighting those who are always in effective positions to receive and redistribute possession (Ievoli, 2023). These metrics go beyond traditional counts of passes or shots by revealing the structural importance of a player in the team's passing network, even if their individual statistics appear modest. Unlike basic statistics such as pass count or distance covered, which treat each event equally, centrality metrics incorporate the context and structure of play, revealing which players are tactically central to team movement and connectivity (Travassos et al., 2023). This makes them particularly useful for identifying undervalued roles—such as a deep-lying playmaker or inverted full back—whose contribution may not stand out in traditional box-score metrics (Sarmento et al., 2018).

2.2 Social Network Analysis – ‘Golden Index’

Social Network Analysis (SNA) has been widely used in football research to assess team and player performance. This technique ranks influential players based on their structural importance within the team, using concepts and tools from graph theory. However, the definition of a "key player" varies across studies. Some define key players as those who significantly influence team interactions and organise attacking sequences (Grund, 2012), while others focus on players who frequently contribute to decisive outcomes such as goals or assists (Mendes, 2015; Pereira, 2019). For instance, in their analysis of Real Madrid's attacking play during the 2011/12 season, Barbosa et al. (2016) found that passing and receiving were the most frequent actions in the offensive phase, accounting for over 60% of attacking sequences. In contrast, during the finalisation phase—the segment of play leading directly to goal attempts—dribbling (21.9%), crossing (17.3%), and shooting (25.4%) were identified as the most prominent technical actions. This quantification highlights how different behaviours contribute to different phases of attack, with collective build-up play relying heavily on distribution, while goal completion often depends on individual actions that disrupt defensive lines.

Despite advancements in SNA, most studies focus primarily on passing networks and often overlook other key technical actions, such as dribbling. Moreover, there is currently no singular statistic that integrates multiple technical-tactical indicators with SNA. This limitation was addressed by Pereira et al. (2019), who introduced the Golden Index (GI)—a composite formula that combines both SNA-derived and conventional performance metrics to better evaluate individual player contributions. A set of variables related to player performance had to be chosen, defined, and validated to build the GI formula. To guarantee the relevance and accuracy of the variables used to quantify player performance in football attacking plays, Pereira and colleagues employed a multi-step approach for selecting variables for the GI formula.

2.2.1 Creating the Golden Index

This procedure included a thorough literature review followed by expert validation. The authors started by doing a thorough analysis of the literature to find performance measures that were previously used to evaluate players' individual and team contributions in football. This assessment covered advanced measures from SNA, such as betweenness centrality, page

rank prestige, and proximity centrality, in addition to standard statistics like assists, goals, successful dribbles, and passes. These SNA measures were selected because they provide a more comprehensive view of a player's role in attacking plays by assessing the player's influence inside the team's passing network (Clemente et al., 2015). The authors created a questionnaire to get professional opinions on the significance and weighting of every variable after compiling a list of possible factors. A panel of football specialists, chosen for their vast experience and in-depth knowledge of the game, received this questionnaire. To identify which variables were most important to include in the GI formula, the questionnaire asked experts to rank each variable's value on a Likert scale. The completed questionnaires were examined with a consensus threshold of 75% agreement among respondents, and the expert panel strongly supported each variable included in the final formula (Pereira et al., 2019).

Data from the 2016/17 season of Club Atlético de Madrid was used to validate the GI formula. The highest-scoring players based on the GI were Koke, Yannick Carrasco, and Filipe Luís, while lower scores were recorded for Lucas Hernández, Stefan Savić, Diego Godín, and Fernando Torres. These rankings reflect the distribution of involvement in attacking actions across the squad during that season. To compare the GI with other established platforms, players such as Koke and Carrasco also received high ratings on WhoScored for the same season, based on metrics such as key passes, dribbles, and assists. While platforms like WhoScored and SofaScore use proprietary algorithms and aggregated performance data across phases of play, the GI was designed to focus specifically on the attacking phase. Its construction includes input from expert coaches and incorporates variables drawn from SNA and traditional performance statistics (Pereira et al., 2019; Clemente et al., 2021).

Pereria's study emphasises the importance of combining objective measurements with subjective expert assessments to evaluate player performance. While objective data offers consistency and quantifiable insights, it may overlook context-specific nuances such as tactical intent or positional responsibilities. Subjective input from experienced professionals helps account for these factors, offering a more complete and practical understanding of a player's contribution within the team structure.

2.3 Defensive Golden Index

Later research by Ferreira et al. (2021) followed the same process to that of Pereira et al. (2019) of evaluating and ranking football players performances, although this research focused on ranking players on the defensive phase of the game instead of the attacking phase. Ferreira and colleagues' study fills a major void in sports statistics as offensive statistics frequently eclipse defensive actions. The outcome of this research was the development of the Defensive Golden Index (DGI).

The DGI's foundation is based on several sports' performance analysis theories. Understanding individual and team performances during football games is mostly dependent on tactical behaviours and match analysis. According to Kormelink and Seeverens (1997), traditional research and approaches frequently concentrate on a simple notational examination of defensive actions, such as the quantity of tackles or interceptions, yet these metrics provide only a partial view of a player's defensive contribution. Castelo (2009) emphasised that to obtain a complete understanding of player performance, it is important to analyse defensive and attacking behaviours simultaneously. This study also refers to previous studies, such as Carling (2007), that emphasise the significance of individual player contributions to the tactics and results of the team. Barreira et al. (2014) noted that offensive measures have been the subject of much research, but there is a lack of literature devoted to defensive analytics.

To provide a reliable and accurate evaluation of defensive performance in football, a thorough procedure combining theoretical study and real-world experience resulted in the creation of the DGI (Ferreira, 2021). A comprehensive literature analysis on football performance measurements was the first step in the variable selection process and research by Kormelink and Seeverens (2001), Carling et al. (2007), and Freitas (2023) provided valuable insights. Crucial elements of successful defensive performances were identified through a combination of literature reviews and practitioner experience, including tackles, interceptions, and one-versus-one (1v1) defensive situations. This initial list of variables was refined based on the authors' professional background as coaches and analysts, with practical insight helping to ensure their relevance. To formally validate these selections, a structured survey was conducted with eleven football specialists selected for their extensive coaching and performance analysis experience. These experts reviewed the proposed variables,

confirmed their applicability, and provided input on how each should be weighted according to its significance in successful defensive play.

The final set of variables included tackles, representing a player's ability to dispossess opponents; anticipation, reflecting proactive defensive behaviour; successful interceptions, indicating positional awareness and game-reading skills; 1v1 defensive actions, showcasing individual proficiency in critical situations; and clearances and aerial duels, which are essential for managing aerial threats and removing danger from high-risk areas. Each variable was selected to represent a distinct and essential aspect of defensive performance. To allow for fair comparisons across players and contexts, all variables were standardised by adjusting for playing time, subtracting the mean value of each variable across all players, and dividing by the standard deviation of that variable across all players (Ferreira et al., 2021). This ensured consistent and objective evaluation, regardless of individual match conditions or minutes played.

In the second stage of the study the DGI formula was applied to rank Fútbol Club Barcelona players for the 2018/19 La Liga season. Using the DGI, Sergio Busquets, Clément Lenglet, and Gerard Piqué emerged as Barcelona's top defensive performers during the 2018/19 La Liga season. Busquets led the rankings with consistently high scores across key variables such as anticipation, successful interceptions, and 1v1 duels, reflecting his central role in disrupting opposition play and initiating recovery. Lenglet and Piqué followed closely, both demonstrating strong aerial ability and positional discipline, particularly in matches against top-tier opponents such as Atlético Madrid and Sevilla, where defensive contributions were critical to match outcomes.

The results of this study are consistent with those of Liu et al. (2015), who found that successful defensive actions—particularly interceptions and tackles—were statistically associated with improved match outcomes, including higher win probabilities and reduced goals conceded. Similarly, the DGI highlights these same actions as core contributors to overall defensive performance, reinforcing the idea that proactive and effective defending is a key determinant of team success. By integrating these actions into a weighted, standardised index, the DGI builds on Liu et al.'s findings by providing a structured framework for evaluating defensive impact on a player-by-player basis.

The DGI creation and application represent a substantial breakthrough in the study of sports performance analysis. The DGI can help coaches, analysts, and researchers better understand and improve defensive strategies and player performances by offering a thorough and standardised technique to analyse defensive activities. To further evaluate the index's efficacy, future studies may build on this methodology by adding more variables and using it across teams and leagues. The study emphasises the crucial role that defensive metrics play in attaining competitive success, adding to the growing body of literature that aims to improve the analytical tools available for football performance analysis.

2.4 Notational Analysis & Position-specific KPIs

Moneyball is a baseball term that refers to the idea of using statistical analyses to find undervalued players and create competitive teams whilst minimising financial implications. To apply this idea to football, Hughes et al.'s (2012) examined elite male football players' key performance indicators (KPIs) across a variety of positions. The main objective was to create a collection of uniform KPIs that would help teams and clubs' management in scouting, profiling, and player development.

There is a well-established tradition of notational analysis in sport, particularly in football, where it has served multiple purposes. Hughes and Franks (2004) identified five core objectives of notational analysis: movement analysis, instructional support for coaches and players, tactical evaluation, database development, and technical performance assessment. Movement analysis, first explored by Reilly and Thomas (1976), involves examining players' movement patterns and physical effort across positions, which can inform position-specific training programmes for instructional use. Franks (1997) and Hughes (2004) demonstrated that providing feedback from notational analysis can significantly enhance learning and performance outcomes. In one study, Hughes and Franks (1997) showed that football players who received notational analysis-based feedback improved their decision-making accuracy by 16% over a six-week training period, compared to only 5% improvement in a control group that received no such feedback.

In terms of tactical evaluation, Yamanaka et al. (1997) applied notational methods to assess team strategies, highlighting tactical differences observed during the 1994 World Cup Asian Qualifiers. Regarding database development, Garganta (1998) stressed the importance of creating performance models to guide training structure and match preparation. Finally,

technical evaluation has been used to identify key differences between performance levels, with Partridge et al. (1993) showing notable distinctions between collegiate and professional players—findings that have implications for coaching and player development strategies.

In early 2011, a panel composed of university faculty members and 51 Sports Science students from nine European institutions—many of whom had practical experience in performance analysis, talent identification, or elite youth coaching—collaborated to develop a structured set of KPIs for football (Hughes et al., 2012). This multidisciplinary panel examined seven playing positions: goalkeepers, centre backs, full backs, central midfielders, attacking midfielders, wide midfielders, and forwards. Through a structured workshop format, they generated position-specific KPIs, which were grouped into five core categories: psychological, tactical, physiological, technical (defensive and attacking), and technological.

Psychological KPIs such as confidence, concentration, resilience, and motivation—were considered universally important. The panel noted that psychological robustness was particularly vital for goalkeepers and centre backs, who frequently operate under high-stress, game-defining situations. These roles require composure, especially when responding to transitions or handling set-piece pressure. Recent research highlights that psychological coping skills and mental resilience significantly differentiate goalkeepers and defenders, underpinning consistent match performance under pressure (Pires et al., 2025).

Tactical KPIs involved spatial awareness, decision-making, and understanding of team structure. Midfielders were expected to exhibit strong communication and organisational skills to manage transitions between defence and attack. Full backs were highlighted for their off-the-ball movement and ability to follow specific tactical instructions such as overlapping or underlapping runs. Central defenders needed to demonstrate positional discipline and anticipation to maintain compactness and cover depth. These tactical indicators align with recent findings showing that superior decision-making and tactical awareness support more effective team organisation and positional efficiency across roles (Matos et al., 2023; Dambroz et al., 2023).

Physiological KPIs were heavily influenced by positional demands. Height and reach were especially emphasised for goalkeepers and centre backs. Slimani et al. (2019) confirmed that elite goalkeepers and central defenders were significantly taller than players in other positions—often averaging over 188 centimetres—due to the aerial responsibilities and

physical dominance required in defensive zones. Taller stature provides advantages in winning aerial duels, defending crosses, and claiming high balls in goalmouth scenarios. Conversely, wide players and midfielders prioritised attributes like agility, aerobic capacity, and acceleration to exploit space and maintain high-intensity movements over longer durations. Recent positional profiling studies reaffirm these anthropometric and aerobic distinctions between defensive and attacking players (Parpa and Michaelides, 2022).

Technical KPIs were split between attacking and defensive skillsets. Defensive KPIs included pressing, tackling, defensive positioning, and aerial duel success. For goalkeepers, this expanded to shot-stopping, recovery movements, and distribution under pressure. On the attacking side, KPIs such as passing accuracy, dribbling success, and shot conversion rate were highlighted as essential for midfielders, wide players, and forwards. The panel noted the growing importance of multifunctional technical profiles, particularly in roles like inverted full backs and box-to-box midfielders. These trends are supported by evidence identifying key technical performance indicators—such as passing efficiency and shooting accuracy—as predictors of match success (Stafylidis et al., 2024).

Technological KPIs, while not position-specific, reflected the increasing integration of global positioning systems (GPS), video analysis, and wearable technology tracking and optimising individual and team performance. These tools enabled more precise monitoring of physical loads, technical outputs, and tactical behaviour in training and match contexts. This structured framework provided a foundational model for understanding how technical, physical, and psychological traits vary by position and supported the application of objective metrics in talent development, scouting, and match preparation. Recent studies highlight that performance analysis and wearable tracking systems are now integral to contemporary coaching and player monitoring practices (Davidson et al., 2024; Ferraz et al., 2023).

2.4.1 The Use of KPIs in Football

By creating position-specific KPIs, this study effectively applies the Moneyball methodology to football and provides a structured framework for evaluating player performance beyond subjective observation. The creation of these KPIs offers a well-organised framework with numerous useful football applications. These metrics help coaches and scouts assess player performance more objectively, which supports match training and hiring practices to the unique requirements of each position. Standardising KPIs also facilitates the development of

a consistent vocabulary for talking about player characteristics and future advancements. These KPIs enable clubs to quantify technical, tactical, psychological, and physiological traits across positions, allowing for more objective comparisons between players. When integrated into scouting and recruitment processes, these metrics help identify undervalued players who possess critical attributes that align with a team's tactical identity—even if those players may not stand out using traditional statistics.

In terms of coaching and development, KPI frameworks support targeted training interventions by highlighting individual strengths and weaknesses relative to positional benchmarks. This data-driven approach helps coaches design bespoke development plans and track longitudinal progress over time. Additionally, by standardising the language and metrics used in evaluation, KPI implementation fosters clearer communication across multidisciplinary teams, from analysts and coaches to recruitment staff and sport scientists. Ultimately, embedding KPIs into coaching and management workflows improves the accuracy and consistency of decision-making across talent identification, squad planning, and performance review. It reduces reliance on subjective judgement alone and increases the likelihood of evidence-based decisions that align with both short-term competitive goals and long-term player development strategies.

As team tactics evolve, the KPIs in football are continuously shifting. Therefore, it is essential to develop a team-specific index, as each club and position have distinct technical and tactical requirements. The modern evolution of the full back role illustrates this clearly. Traditionally, full backs were responsible for defending against opposition wingers and providing width by supporting attacks down the wing. However, recent tactical developments, such as the “inverted full back” approach, have redefined this position (Konefał et al., 2019). Managers like Pep Guardiola now deploy full backs in more central areas during possession, allowing them to act as additional midfielders and contribute to ball progression (Tierney, 2021).

To succeed in this role, players must not only possess strong defensive qualities but also demonstrate technical vision—the ability to scan the pitch, anticipate passing lanes, and make forward-thinking decisions under pressure. This involves reading play effectively, identifying opportunities to advance possession, and maintaining composure when linking defensive and attacking phases (Kusuma, 2023). Such qualities emphasise how positional demands evolve

over time, reinforcing the need for indices that reflect both the tactical context and specific performance requirements of each position.

2.5 Coach Evaluation of Position-Specific Technical Skills

While performance indices and position-specific KPIs offer structured approaches to player evaluation, coaches' subjective judgments remain central to both development and selection processes. Recent research — particularly the work of Barraclough et al. (2023) — has shown that these judgments are not uniform but vary systematically across positions and, importantly, between coaches. In their study of academy coaches, Barraclough and colleagues aimed to develop a shared mental model of performance by identifying which technical actions were considered most decisive for each role. They found that defensive players were primarily judged on 1v1 duels, interceptions, and aerial dominance; wide players on dribbling and crossing; and central midfielders on first touch, composure, and distribution under pressure. Certain actions, such as ball control, were viewed as important across multiple positions, yet the relative importance (or weighting) of each action depended heavily on positional role and tactical philosophy. Crucially, the study also revealed considerable between-coach variability. For example, some coaches placed greater emphasis on secure possession and short passing, while others prioritised direct play, progressive actions, or creativity in attacking areas of the pitch (i.e., near the opponent's goal). The authors note that academy context (e.g., category 1 vs lower-category clubs) also influenced the criteria used, with resource-rich environments able to incorporate more nuanced assessments. These findings underscore the value of position-specific evaluation and demonstrate that player appraisal is shaped as much by coaching philosophy and context as by objective performance (Mujika et al., 2018).

Complementary research confirms that technical assessments are generally effective at distinguishing between levels of player ability, but the metrics employed often fail to capture context or role-specific nuance. Koopmann et al. (2020) conducted a systematic review of 59 studies and reported that 93% of technical assessments were discriminatory, explanatory, or predictive of player quality, yet most relied on outcome-based measures (e.g., pass accuracy, dribble success) in controlled settings. Such assessments, while useful, do not reflect how coaches differentiate between technical actions in match scenarios. For example, while pass accuracy is valued across all roles, some coaches prioritise retention under pressure, whereas others emphasise line-breaking or penetrative passes. This highlights why coaches may differ

in their evaluations, even when discussing the same skill, and why integrating coach perspectives is critical to achieving a context-sensitive understanding of performance. These principles underpin the rationale for the current study, which elicited coach ratings of technical skills by position.

Work focused explicitly on academies echoes these themes. McCalman et al. (2025) found that academy coaches consistently stressed technical proficiency under pressure—including first touch, dribbling, and distribution—as key markers of skilfulness, but the relative importance varied between individuals, reflecting different tactical preferences and developmental philosophies. Similarly, studies on talent identification demonstrate that coaches tend to rate technical skills and game understanding more highly than physical attributes, but again with differences in how these are weighted depending on environment and selection pressures (Abate Daga et al., 2024). Collectively, this body of work indicates that any robust evaluation model must (i) account for positional demands, (ii) surface and respect coach-driven weightings, and (iii) remain sufficiently transparent to capture and compare different viewpoints.

2.6 Player Performance Assessment Tools

There are several platforms and systems used to assess player performance, with OPTA being one of the most prominent data providers. OPTA is a reputable sports analysis company that records over 3,000 player actions per game, such as passes, shots, and tackles, documenting precise details like the individuals involved, timing, and outcomes. This data is collected through a combination of automated methods and manual analysis by skilled professional analysts, with video footage examined to ensure accuracy and completeness. OPTA applies a complex weighting system to the collected data, giving higher importance to impactful actions like goals and assists, while considering contextual factors such as opposition strength and the timing of events (OPTA Sports, 2025).

While OPTA provides raw data and its own grading system, known as OPTA Points, numerous publicly accessible football analytics platforms—such as WhoScored, FlashScore, and FotMob—use OPTA data to generate player ratings and match summaries for media, fan engagement, and performance comparison (WhoScored, 2025; FlashScore, 2025; FotMob, 2025). These platforms translate OPTA’s raw statistics into simplified rating metrics that present complex data in an accessible format for general audiences. SofaScore, however,

stands out as it uses a proprietary grading system that does not rely exclusively on OPTA data, instead incorporating over 200 performance parameters sourced from multiple providers to produce composite player scores (SofaScore, 2025). This approach can be advantageous, as it allows for a more flexible evaluation framework that integrates diverse data inputs, but it also makes direct comparison with OPTA-based systems more difficult due to differences in variable definitions and weighting.

Each platform employs distinct methodologies and algorithms, resulting in variations in player grades. Despite the accuracy of OPTA's metrics and the breadth of analyses provided by these platforms, there is no single universal grading system deemed the most reliable. Moreover, the confidentiality of these grading algorithms makes it challenging to understand the specific factors influencing player scores or to use them as tools for targeted player development (Kalenderoğlu, 2019). The limitations of a standardised formula for grading players across different clubs and tactical systems also impact the accuracy of the results, as varied playing styles can influence grades differently. Additionally, OPTA does not track data for academy games, which are critical for evaluating and nurturing young talent. These constraints highlight the need for more flexible and transparent systems to support both player assessment and development.

2.7 How to be Successful in Football

Despite decades of performance analysis, it remains difficult to pinpoint a definitive set of variables that determine success in football. To address this gap, Lepschy, Wäsche, and Woll (2018) conducted a systematic review analysing 68 empirical studies published up to 2016. The authors identified 76 distinct performance indicators across technical, tactical, and physical domains, highlighting the multifactorial nature of football performance. Their findings revealed several variables most consistently associated with successful match outcomes.

First, efficiency, defined as the goals-to-shots ratio, emerged as the most critical determinant of success. Across multiple studies, more efficient teams—those converting a higher proportion of attempts—consistently achieved superior results, with significant differences in goal efficiency observed between winning and losing teams (Szwarc, 2007; Broich et al., 2014; Yue et al., 2014; Lepschy et al., 2018). Shots on goal were also strongly correlated with success, with winning teams typically producing a greater number of accurate attempts

than losing teams. Finally, ball possession showed a generally positive, though context-dependent, relationship with success. While higher possession rates were often linked to winning outcomes—particularly among top-ranked teams—their influence diminished once team strength and tactical approach were considered.

Collectively, these findings indicate that while volume-based metrics such as possession and total shots provide useful context, it is the quality and efficiency of execution, particularly during attacking phases, that most reliably predict successful performance.

2.8 The Use of Performance Tracking to Develop Academy Players

Coaches can effectively support a player's development in specific areas—such as technical proficiency, physical fitness, and tactical awareness—by consistently tracking their performance over time. This data enables practitioners to identify both strengths and areas for improvement, with greater objectivity than subjective observation alone. For example, repeated assessment of technical skills like passing accuracy or 1v1 success rate can highlight whether a player is progressing as expected or requires targeted intervention. Similarly, physical metrics such as sprint speed, endurance, or injury risk indicators can inform the conditioning and recovery protocols needed for safe development. On the tactical side, performance data from game scenarios (e.g., positioning during transitions or pressing efficiency) can help players better understand their decision-making processes and game intelligence (Sarmiento et al., 2018).

Crucially, this data-driven insight is particularly valuable during a player's formative years when learning capacity and development potential are deemed highest. By tailoring individual development plans to reflect the unique profile of each player, coaches can set personalised objectives, track progress toward goals, and adjust training loads or focus areas accordingly. This approach not only promotes more efficient long-term development but also aligns with best practices recommended by national governing bodies such as The English Football Association which emphasises evidence-based, individualised planning for youth players (Layton, 2023).

Performance data helps to reduce biases that can arise with subjective assessments by providing a factual basis for player evaluations. This guarantees that decisions about team selection and team roles are made based on performance. Accountability and motivation are

two further factors that emphasise the value of academy player performance tracking. Tracking an athlete's performance can be a useful tool for motivating them to maintain or even enhance their technical and physical performance levels. Berntzen et al. (2025) conducted research that demonstrates the psychological benefits of performance tracking. The study indicated that athletes' motivation and engagement in their training regimens are enhanced when they receive regular feedback on their performance.

Coaches and scouts can objectively determine which players have the potential to achieve at higher levels by keeping track of players' performances. Tracking performance variables like technical proficiency, match contributions, and physical conditioning consistently helps identify future elite athletes early. Johnston (2018) explored the function of objective data in the early identification and continuous evaluation of talent. This method makes talent identification more trustworthy and effective by ensuring that it is based on performance and merit rather than subjective opinion.

Finally, benchmarking performance data against peers is another factor that emphasises the importance of player performance tracking at academy level. By comparing individual metrics—such as technical skills, physical fitness, and game performance—coaches can identify standout talent who excel and may be ready for advanced opportunities. This comparison also highlights areas where players may need additional support, allowing for tailored development plans to address specific weaknesses. Furthermore, benchmarking informs decision-making regarding player progression and resource allocation, ensuring that development efforts are focused effectively. Such comparative analysis is critical for both recognising top performers and supporting those who require further improvement (Kelly et al., 2020).

2.9 Summary and Research Rationale

The literature reviewed highlights the increasing importance of performance tracking in supporting the holistic development of academy players. Objective data allows coaches to assess technical proficiency and physical conditioning with greater precision, ensuring that training and development decisions are grounded in measurable evidence rather than subjective opinion. When used effectively, this information enables more individualised training approaches, promotes accountability, and enhances the long-term progression of young players (Berntzen et al., 2025; Kelly et al., 2020).

Despite these advancements, a clear gap remains in understanding how coaches themselves interpret and prioritise the technical components of player performance. While prior studies have examined individual performance indicators, limited attention has been given to the subjective weighting that coaches assign to these variables across different playing positions. This is a crucial omission, as coaches' perceptions ultimately shape how data is interpreted and how developmental priorities are established within academy environments.

To address this gap, the present study focuses on understanding how technical performance is valued differently across positions, skill types, and coaching perspectives. By analysing how coaches rate the importance of specific technical actions for various positional roles, the study captures the nuanced ways in which performance expectations differ throughout the pitch. It also explores how individual coaching philosophies and experiences influence these evaluations, recognising that player assessment is not uniform but shaped by multiple contextual factors.

In line with this purpose, the study has two primary aims: first, to explore which technical performance metrics football coaches consider most important for each playing position; and second, to examine how these perceptions differ among coaches and how they align or contrast with existing research. As part of this process, a new model—the Game Performance Index (GPI)—was developed to visualise coach-rated variable importance across positions. While not a validated measurement tool, the GPI serves as a conceptual framework designed to structure comparisons and provide a foundation for future refinement in objective player evaluation

3.0 Methodology

3.1 Study Design and Overview

This study followed a multi-stage process similar to previous research that developed composite performance indices in football (e.g., Pereira et al., 2019; Ferreira et al., 2021; Barreira et al., 2014; Prudente et al., 2004).

Stage 1 involved the selection and operational definition of technical performance variables, which were incorporated into a validation questionnaire.

Stage 2 included both a pre-expertise evaluation, where experts reviewed variable relevance by position, and an expertise evaluation, where experts rated the importance of each variable to establish positional weightings. Together, these steps provided insight into how different technical actions are prioritised across roles.

Stage 3 applied statistical analysis and standardisation techniques to the expert ratings, from which the Game Performance Index (GPI) formulas were established and then applied to match data.

In the present study, the Game Performance Index (GPI) is not presented as a validated or predictive performance metric. Instead, it is conceptualised as a demonstration framework designed to illustrate how expert-rated positional importance can be embedded into a structured, position-specific scoring model. The application of the GPI to match data serves an illustrative purpose only, showing how coach perceptions may be operationalised in practice rather than claiming to provide definitive or generalisable player evaluations. The sequence of stages undertaken in the development of the GPI is illustrated in *Figure 1*.

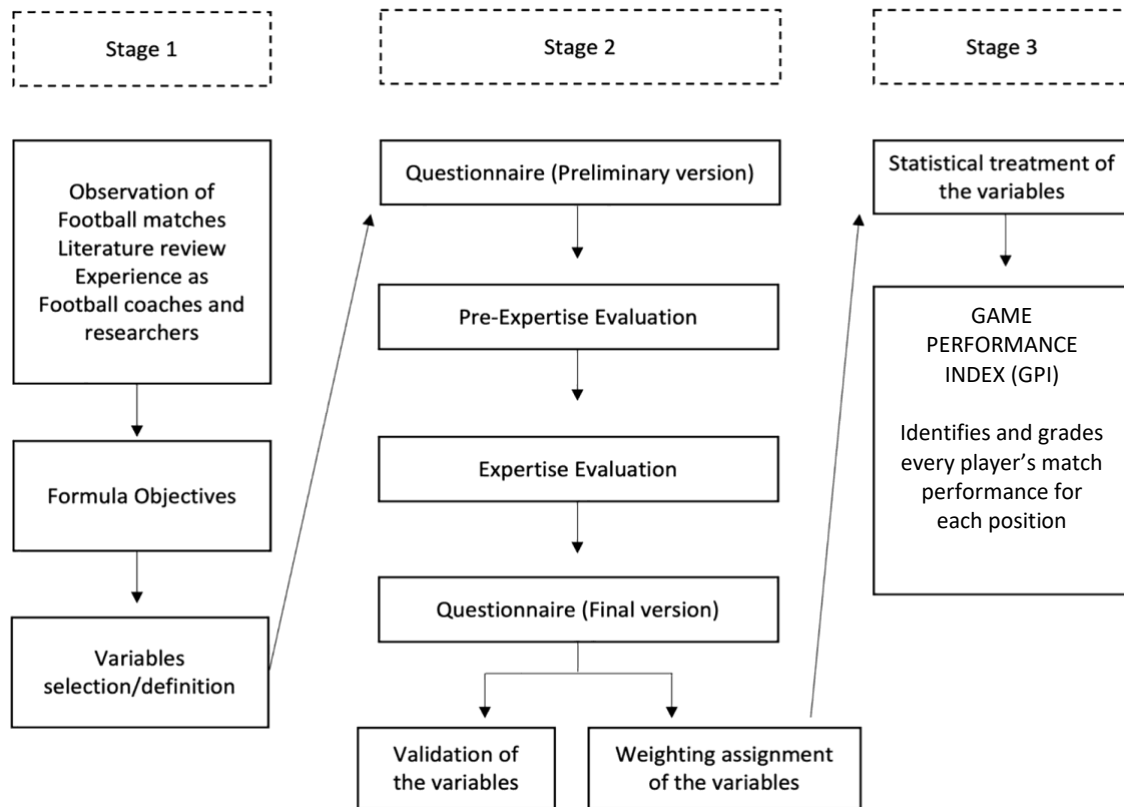


Figure 1. Steps taken in the development of the Game Performance Index (GPI) formula adapted from the Defensive Golden Index (Ferreira, 2021) and the Golden Index (Pereira, 2019)

3.2 Data Collection

Technical performance data were extracted using professional football performance analysis platforms, namely Hudl Sportscode (integrated with Wyscout), for all competitive fixtures played by Rangers Academy's Professional Development Phase (PDP) teams during the 2023/24 season. The dataset covered 30 matches in total—15 from the U18 squad and 15 from the B Team—with observations recorded for 23 players who featured across these fixtures. To ensure meaningful positional comparison and reduce distortion caused by limited match exposure, only player performances involving a minimum of 45 minutes played were included within the dataset. This threshold was applied to avoid the inclusion of short substitute appearances, which may not provide representative technical performance data relative to positional responsibilities. Each player was assigned a positional ID code (e.g., CB1, FB2, etc.) to ensure consistent anonymisation and position-based comparison, representing 4 centre backs (CB), 4 full backs (FB), 3 defensive midfielders (DM), 5 attacking midfielders (AM), 4 wingers (W), and 3 centre forwards (CF). In addition to the event data captured through Wyscout and Sportscode, each player wore a GPS tracker unit

(Catapult S7 Vector Melbourne, Australia) during matches. This wearable technology was used to accurately record individual match minutes and participation time, ensuring that all technical actions were contextualised relative to verified playing duration. The inclusion of this data allowed for precise ratio-adjustment of variables by time played, strengthening the reliability of subsequent comparisons across players and positions.

The dataset comprised a broad set of positive and negative technical actions, coded in line with Wyscout's event definitions. Variable selection was guided by prior research (e.g., Pereira et al., 2019; Ferreira et al., 2021), aligned with industry practice (e.g., Opta-style metrics), and consistent with frameworks commonly applied within elite academies.

The central purpose of collecting these data was to provide the foundation for analysing how coaches value different technical actions across positions. To this end, seven experienced coaches and analysts from Rangers Football Club were recruited to rate the importance of each variable for six outfield positions using a five-point Likert scale (see Stage 2). Their responses were used to examine agreement levels between experts, compare positional differences in technical priorities, and identify variation across individuals.

Based on these evaluations, position-specific formulas were created, embedding the expert-derived weightings into the calculation. These formulas formed the basis of the Game Performance Index (GPI), which in this study is conceptualised as a framework for applying coach perceptions directly to real match data. The formulas were applied to the 23 players across the 30 matches, with each performance graded according to the positional formula corresponding to the role played in that fixture.

3.3 Participants

Seven participants took part in both the pre-expertise and expertise evaluations. All were experienced coaches or analysts with direct involvement in Rangers FC's Professional Development Phase (PDP).

The selection of the board of experts followed established criteria adapted from Ferreira et al. (2021) and Barreira et al. (2014), with inclusion requiring at least two of the following three standards to be met:

- i) possession of a UEFA B coaching licence or higher;

- ii) at least two years of coaching or performance analysis experience within a PDP team;
- iii) a minimum of eight years working in professional football.

Participants were aged 24–39 years, with 2–10 years of experience at Rangers FC, ensuring that perspectives reflected both depth and breadth of applied expertise. Recruitment was facilitated by the researcher’s active role within the club, which allowed for in-person engagement, clarification of study purpose, and efficient consent procedures.

3.4 Position Characteristics

Distinct position-specific formulas were required because technical demands vary considerably across roles on the pitch. For example, the qualities needed for a centre back differ greatly from those required of a winger or attacking midfielder. Drawing on Hughes et al. (2012) and consultation with experienced coaches, six outfield positions were selected for analysis: Centre Back (CB), Full Back (FB), Defensive Midfielder (DM), Attacking Midfielder (AM), Winger (W), and Centre Forward (CF). These roles were chosen to represent contrasting technical responsibilities in and out of possession and are summarised in *Table 1*.

Goalkeepers were excluded due to the highly specialised nature of their position and the distinct skill set it requires.

Table 1. Characteristics needed to perform each position effectively both in possession and out of possession

Position	Overall	In Possession	Out of Possession
Centre Back	Defensive play, Heading Capabilities	Support build-up play	Mark players, controlled defending
Full Back	Defensive play, crossing, 1v1 play, Physical conditioning	Good cross delivery, Add support and structure	Cut out cross, 1v1 defending
Defensive Midfielder	Defensive play, running, passing	Don’t run with ball too much, switch play	Control play, mark a player
Attacking Midfielder	Technical skills, passing, creativity, shooting	Add support. Get into scoring positions	Support, defensive thinking

Winger	Physical conditioning, 1 to 1 play	Good cross delivery, Score goals	Cut out crosses, tuck in to mark
Centre Forward	Velocity, 1 to 1 play, shooting	Score goals, hold up play	Keep opponents in front of you

3.5 Stage 1 – Selection and definition of variables

A comprehensive list of technical variables was collated in collaboration with Rangers FC coaches and analysts, using Hudl Sportscode and Wyscout as the coding framework. All variables included in the study were already being routinely collected and monitored within Rangers' internal performance analysis processes, ensuring consistency with the club's existing data practices. Informal discussions with coaches and analysts during this stage helped confirm the practical relevance of each variable and its alignment with the club's terminology and workflow. Because Wyscout terminology is widely recognised, all operational definitions in this study align with Wyscout, allowing the dataset and subsequent analyses to be directly linked back to the club's existing performance data.

Variables were grouped into positive or negative contributions (e.g., progressive pass [successful/unsuccessful], dribble [successful/unsuccessful], defensive duel [won/lost]). The inclusion of negative variables was important to capture the risk–reward balance inherent in football performance. For instance, an unsuccessful dribble or misplaced progressive pass may carry tactical costs such as conceding possession or leaving the team vulnerable to counterattack. Considering both positive and negative contributions therefore reflects not only the benefits of successful actions but also the potential impact of errors, providing a more realistic representation of player performance.

Table 2. Description of the variables proposed in the pre-expertise.

Variable	Description
Aerial duel (won/lost)	When two or more players from opposing teams jump to compete for the ball. (An aerial duel is considered won in favour of the player who touches the ball first, no matter what happens next. An aerial duel that results in a foul is considered won in favour of the player who suffered a foul)
Assist	The last action of a player from the goalscoring team, prior to the goal being scored by a teammate, or an own goal.
Defensive duel (won/lost)	When a player attempts to dispossess an opposition player to stop an attack progressing. (If the defensive player stopped the progression of the attacking player with the ball and didn't commit a foul, the defensive duel is considered won)
Dribble (successful/unsuccessful)	An attempt to move past an opposing player whilst trying to maintain possession of the ball.
Dribble past attempt (successful / unsuccessful)	An attempt to prevent an opposing player in possession of the ball to dribble past the player. If the defensive player stopped the progression of the attacking player with the ball and didn't commit a foul, the dribble past attempt is considered won for the defender
Fouls performed that originated dangerous situations	Number of times that a defending player commits a foul that directly causes a dangerous situation to the defending team, at the level of the ball arrival in the first defending third of the pitch, during a football game (adapted from game laws of football)
Fouls performed that originated non-dangerous situations	Number of times that a defending player commits a foul that directly cause a non- dangerous situation to the defending team, at the level of the ball arrival in the first defending third of the pitch, in the course of a football game (adapted from game laws of football)
Interception (successful / unsuccessful)	An act of player actively intercepting the ball by anticipating its movement when the opponent is shooting, passing or crossing.
Loose ball duel	A duel for a loose ball, when no team has clear ball possession. (Neither of the players involved have a clear advantage of reaching/touching the ball first)
Opportunity	A clear chance of scoring a goal.
Pass to final third (successful / unsuccessful)	Any pass that originates outside of the final third and the next ball touch occurs within the final third. A pass into final third is considered successful if the next touch of the ball is by a teammate.
Pressing duel	When a player moves to apply pressure on an opposing player who is in possession of the ball but doesn't make physical or ball contact.
Recovery	Any Action that ends a Possession of the opposition team (the last action of this possession is a Loss) and starts a Possession for other team.
Shot (on target)	A shot on target faced by the goalkeeper.
Shot (off target)	A shot off target which goes wide or over the bar.
Shot (blocked)	A shot blocked by an outfield opposition player.
Shot (goal)	An attacking player scores a goal. The ball passes over the opponent goal line, between the goalposts and under the crossbar, with no previous violation of the game rules

Progressive pass (successful / unsuccessful)	A forward pass that attempts to advance a team significantly closer to the opponent's goal. A pass is considered progressive if the distance between the starting point and the next touch is: (at least 30 meters closer to the opponent's goal if the starting and finishing points are within a team's own half ; at least 15 meters closer to the opponent's goal if the starting and finishing points are in different halves; at least 10 meters closer to the opponent's goal if the starting and finishing points are in the opponent's half)
Lateral pass (successful / unsuccessful)	A sideward pass that does not break through any opposition lines.
Forward pass (successful / unsuccessful)	A forward pass which does not meet the definition of 'progressive'.
Yellow card	Disciplinary action by the referee that is indicated by showing a yellow card according to law 12.3 of the IFAB Laws of the Game.
Red card	Disciplinary action by the referee that is indicated by showing a red card according to law 12.3 of the IFAB Laws of the Game.
Error leading to opposition chance	An error which directly leads to an opposition opportunity

3.6 Stage 2 – Expert Evaluations

Stage 2 consisted of two linked evaluations, the pre – expertise evaluation and the expertise evaluation:

3.6.1 Pre-expertise Evaluation

Seven coaches and analysts from Rangers FC's Professional Development Phase (PDP) participated in the pre-expertise evaluation. All were experienced practitioners with direct involvement in the club's performance analysis processes. This stage aimed to review the clarity, accuracy, and practical relevance of the operational definitions used for each technical variable.

Participants examined the full list of variables and their accompanying definitions to ensure consistent interpretation across positions and alignment with the terminology used in Rangers' internal coding system. Informal discussions were also held during this process to confirm that each variable reflected those already being collected within the club's performance analysis framework, allowing the dataset to be linked back to existing player records.

Based on participant feedback, minor revisions were made to several definitions to improve precision and reduce ambiguity. Three additional variables were also proposed: chance created, passes per defensive action (PPDA), and tactical yellow card. Following group deliberation, chance created was adopted (replacing assist), as it more accurately isolates the contribution of the passer. In contrast, PPDA and tactical yellow card were excluded due to their subjectivity and the difficulty of maintaining consistent measurement. The revised definitions were then finalised for use in the expertise evaluation stage.

3.6.2 Expertise Evaluation

Using the refined list of variables from the pre-expertise stage, the same seven experts proceeded to the expertise evaluation. At this stage, they rated the importance of each variable for every position on a five-point Likert scale, defined as follows:

- 1 = Not Important
- 2 = Slightly Important
- 3 = Important
- 4 = Very Important
- 5 = Extremely Important

The Likert scale format was selected because it allowed experts to express not only whether a variable should be included but also the relative strength of its importance. This provided a more nuanced reflection of coaching priorities, acknowledging that the same action may be regarded as essential for one position but only moderately useful for another.

As in Stage 1, variables were separated into positive and negative contributions to reflect the risk–reward balance in performance. This distinction recognised that unsuccessful actions (e.g., a failed dribble or misplaced progressive pass) do not simply represent the absence of success but often carry distinct tactical costs such as conceding possession or exposing the team to counter-attack.

To determine inclusion within each positional formula, a 70% cohort agreement threshold was applied, meaning a variable was retained if at least five of the seven expert coaches rated it as important (≥ 3). This threshold was selected to reflect a strong majority consensus while recognising the subjective and context-dependent nature of coach perceptions within football

performance evaluation. Given that technical priorities may vary according to coaching philosophy, tactical interpretation, and positional understanding, complete unanimity between experts was not considered necessary for variable inclusion. Instead, the threshold was designed to ensure that retained variables reflected broadly shared positional importance across the expert panel while still allowing for some natural variation in professional opinion. The use of consensus-based thresholds is consistent with previous football performance analysis research, including Pereira et al. (2019) and Ferreira et al. (2021), who applied expert-agreement procedures during the development of the Golden Index and Defensive Golden Index respectively. Within the context of the present study, a 70% agreement threshold was considered sufficiently rigorous to support meaningful positional comparisons while remaining appropriate for the exploratory nature of the research and the relatively small specialist sample.

Table 3. Expertise Evaluation (example from participant)

Positive

<i>Variable</i>	<i>Description</i>	<i>CB</i>	<i>FB</i>	<i>DM</i>	<i>AM</i>	<i>W</i>	<i>CF</i>
<i>Aerial duel (won)</i>	<i>When two or more players from opposing teams jump to compete for the ball. (An aerial duel is considered won in favour of the player who touches the ball first, no matter what happens next. An aerial duel that results in a foul is considered won in favour of the player who suffered a foul)</i>	5	5	4	2	1	4
<i>Defensive duel (won)</i>	<i>When a player attempts to dispossess an opposition player to stop an attack progressing. (If the defensive player stopped the progression of the attacking player with the ball and didn't commit a foul, the defensive duel is considered won)</i>	1	5	1	3	5	3
<i>Dribble (successful)</i>	<i>An attempt to move past an opposing player whilst trying to maintain possession of the ball.</i>	5	5	4	2	1	4
<i>Interception (successful)</i>	<i>An act of player actively intercepting the ball by anticipating its movement when the opponent is shooting, passing or crossing.</i>	5	4	3	4	2	2
<i>Offensive duel (successful)</i>	<i>A player in controlled possession of the ball (below elbow height) attempts to pass an opponent, who in turn, is trying to dispossess the player in possession.</i>	1	5	1	3	5	3
<i>Loose ball duel (successful)</i>	<i>A duel for a loose ball when no team has clear ball possession. (Neither of the players involved have a clear advantage of reaching/touching the ball first)</i>	5	5	4	2	1	4
<i>Chance created</i>	<i>A pass leading to a clear opportunity to score.</i>	5	4	3	4	2	2

Pass to final third (successful)	Any <u>pass</u> that originates outside of the final third and the next ball touch occurs within the final third. A pass into final third is considered successful if the next touch of the ball is by a teammate.	1	5	1	3	5	3
Pressing duel	When a player moves to apply pressure on an opposing player who is in possession of the ball but doesn't make physical or ball contact.	5	5	4	2	1	4
Shot (on target)	A shot on target faced by the goalkeeper.	5	4	3	4	2	2
Shot (goal)	An attacking player scores a goal. The ball passes over the opponent goal line, between the goalposts and under the crossbar, with no previous violation of the game rules	1	5	1	3	5	3
Progressive pass (successful)	A forward pass that attempts to advance a team significantly closer to the opponent's goal. A pass is considered progressive if the distance between the starting point and the next touch is: (at least 30 meters closer to the opponent's goal if the starting and finishing points are within a team's own half ; at least 15 meters closer to the opponent's goal if the starting and finishing points are in different halves; at least 10 meters closer to the opponent's goal if the starting and finishing points are in the opponent's half)	5	5	4	2	1	4
Lateral pass (successful)	A sideward pass that does not break through any opposition lines.	5	4	3	4	2	2
Forward pass (successful)	A forward pass which is does not meet definition of 'progressive'.	1	5	1	3	5	3

Negative

Variable	Description	CB	FB	DM	AM	W	CF
Aerial duel (lost)	When two or more players from opposing teams jump to compete for the ball. (An aerial duel is considered won in favour of the player who touches the ball first, no matter what happens next. An aerial duel that results in a foul is considered won in favour of the player who suffered a foul)	5	5	4	2	1	4
Defensive duel (lost)	When a player attempts to dispossess an opposition player to stop an attack progressing. (If the defensive player stopped the progression of the attacking player with the ball and didn't commit a foul, the defensive duel is considered won)	1	5	1	3	5	3
Dribble (unsuccessful)	An attempt to move past an opposing player whilst trying to maintain possession of the ball.	5	5	4	2	1	4
Fouls performed that originated dangerous situations	Number of times that a defending player commits a foul that directly causes a dangerous situation to the defending team, at the level of the ball arrival in the first defending third of the pitch, in the course of a football game (adapted from game laws of football)	5	4	3	4	2	2
Interception (unsuccessful)	An act of player actively intercepting the ball by anticipating its movement when the opponent is shooting, passing or crossing.	1	5	1	3	5	3
Offensive duel (unsuccessful)	A player in controlled possession of the ball (below elbow height) attempts to pass an opponent, who in turn, is trying to dispossess the player in possession.	5	5	4	2	1	4
Loose ball duel (unsuccessful)	A duel for a loose ball, when no team has clear ball possession. (Neither of the players involved have a clear advantage of reaching/touching the ball first)	5	4	3	4	2	2
Pass to final third (unsuccessful)	Any <u>pass</u> that originates outside of the final third and the next ball touch occurs within the final third. A pass into final third is considered successful if the next touch of the ball is by a teammate.	1	5	1	3	5	3

<i>Shot (off target)</i>	<i>A shot off target which goes wide or over the bar.</i>	5	5	4	2	1	4
<i>Shot (blocked)</i>	<i>A shot blocked by an outfield oppositions player.</i>	5	4	3	4	2	2
<i>Progressive pass (unsuccessful)</i>	<i>A forward pass that attempts to advance a team significantly closer to the opponent's goal. A pass is considered progressive if the distance between the starting point and the next touch is: (at least 30 meters closer to the opponent's goal if the starting and finishing points are within a team's own half ; at least 15 meters closer to the opponent's goal if the starting and finishing points are in different halves; at least 10 meters closer to the opponent's goal if the starting and finishing points are in the opponent's half)</i>	1	5	1	3	5	3
<i>Lateral pass (unsuccessful)</i>	<i>A sideward pass that does not break through any opposition lines.</i>	5	5	4	2	1	4
<i>Forward pass (unsuccessful)</i>	<i>A forward pass which is does not meet definition of 'progressive'.</i>	5	4	3	4	2	2
<i>Error leading to opposition chance</i>	<i>An error which directly leads to an opposition opportunity</i>	5	4	3	4	2	2

3.7 Stage 3 – Statistical Analysis and Formula Application

After the validation and weighting of the variables composing the GPI formulas, statistical techniques were applied to establish variable ratios and their standardisation. This ensured that all technical actions contributed proportionally to the composite scores, independent of raw frequency differences across players or positions.

Ratio of variables

Each variable was expressed relative to playing time, with raw counts divided by the minutes played by each player. This approach controlled for unequal match exposure and allowed fair comparisons between players with different playing times.

Standardisation of variables

Standardisation (z-scoring) was applied as a common procedure in descriptive statistics to allow comparison across variables with different units and distributions. The process was completed in three steps:

- Step 1 – Calculating positional means

The mean value for each variable was calculated for each position, using data collected across all 28 variables over 30 matches (15 B Team matches and 15 U18's

matches). Positional means were derived by summing player values within that position and dividing by the number of players.

- Step 2 – Calculating standard deviations

The standard deviation for each variable was calculated across players, providing a measure of dispersion for each variable in relation to the positional mean.

- Step 3 – Standardisation of player values (z-scores)

For each position, each player's time-normalised value was standardised as a z-score by subtracting the positional mean from the player's value and dividing by the positional standard deviation.

Application of the Game Performance Index

The final step involved applying the GPI formulas to the match performances of 23 Rangers U18 and B Team players during the 2023/24 season, using the formula corresponding to the position each player occupied in each match. In total, 30 matches were analysed (15 from the U18 squad and 15 from the B Team). Through the standardisation of variables and the application of position-specific expert weightings, the GPI produced illustrative, comparative composite scores within each positional group. This application was undertaken for demonstrative purposes only; to show how expert-driven perceptions of technical importance may be operationalised in practice and to support player development by highlighting the technical characteristics emphasised for each playing position, rather than to provide definitive or generalisable player rankings

3.8 Stage 4 – Statistical Analysis of Expert Ratings

While Stage 3 applied the GPI formulas to match data, the primary analytical focus of this study was the evaluation of expert ratings. To provide a clear, manageable, and replicable analysis, six representative variables were selected for detailed comparative testing:

- Aerial duel (won)
- Chance created
- Defensive duel (won)
- Shot (goal)
- Dribble (successful)
- Progressive pass (successful)

These six variables were selected because they represented a broad range of technical actions across both attacking and defensive phases of play, while also reflecting key position-specific responsibilities identified within football performance literature (Hughes et al., 2012; Sarmiento et al., 2014). Collectively, they provided representative coverage of defensive effectiveness, attacking output, individual offensive ability, and ball progression/build-up play. The use of a smaller representative subset also improved clarity and interpretability within the inferential statistical analyses, as including the full set of variables would have substantially increased model complexity relative to the available sample size.

Although negative actions were previously acknowledged as important for a complete understanding of player performance, only positive actions were analysed in depth to enable clearer comparison with existing literature, as most prior football performance studies focus primarily on successful or outcome-based technical indicators rather than error-related variables (Hughes & Franks, 2004; Lepschy et al., 2018). The only analysis to include all variables from the full dataset was the participant deviation test, which assessed the degree of variation between individual expert ratings across the entire set of technical actions.

For clarity, the unit of analysis differed across the statistical procedures used in Stage 4. For Fisher's exact tests, each observation represented the distribution of importance ratings for a given technical variable across playing positions. For regression and ANOVA analyses, each observation represented an individual importance rating assigned by an expert to a technical variable. Participant deviation analysis used a single aggregated deviation score per expert, calculated across all variable–position combinations.

3.8.1 Fisher's exact test

Fisher's exact test was used to determine whether the distribution of expert importance ratings (Likert scale 1–5) for each of the six variables differed significantly across positions. This method was chosen due to the small sample size ($n = 7$ experts) and the low expected frequencies in some rating categories, which make chi-squared tests unreliable.

For each variable, a contingency table was constructed with six rows (positions: CB, FB, DM, AM, W, CF) and five columns (Likert scale categories: 1–5). Fisher's exact test was then applied to assess whether the distribution of ratings varied significantly between positions.

A *p*-value of less than 0.05 was considered evidence that the importance of the variable differed significantly depending on positional role.

3.8.2 Participant Deviation Analysis (all variables)

Participant deviation analysis was distinct from the other statistical procedures, as it used the full set of 28 variables across all six positions to capture agreement patterns throughout the entire dataset, rather than focusing on a smaller representative subset. For each participant, an average deviation score was calculated, representing the mean absolute difference between that participant's ratings and the group mean for every variable–position combination. Lower scores indicated that a participant's evaluations were closely aligned with the overall group consensus, while higher scores reflected greater divergence in expert opinion.

Once calculated, these deviation scores were used as a single metric of alignment for each participant. Scatter plots were then produced to explore whether deviation scores were influenced by participant characteristics, specifically age (≤ 25 years vs > 25 years) and length of service at the club (≤ 4 years vs > 4 years). These category thresholds were selected pragmatically to create broadly balanced subgroup distributions within the small specialist sample, allowing exploratory visual comparison between groups. The categories were not intended to represent definitive thresholds of expertise or professional competency, but rather to examine whether increased professional experience or prolonged exposure to the club environment influenced agreement patterns within the expert ratings.

3.8.3 Regression Modelling

Regression modelling was used to test whether skill type significantly predicted expert importance ratings. The analysis focused on six representative technical actions (aerial duel (won), chance created, defensive duel (won), dribbles (successful), progressive pass (successful), and shots (goal)).

A linear regression model was specified with expert rating (1–5 Likert scale) as the dependent variable and skill type as the categorical predictor. Aerial duel (won) was set as the reference category, against which the other five skills were compared. The general form of the model was:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Where:

- Y_i = importance rating for observation i
- β_0 = intercept (mean rating for the reference skill: Aerial duel (won))
- X_i = skill type (dummy-coded, compared to Aerial duel (won))
- ϵ_i = error term

Model fit was assessed using the coefficient of determination (R^2), and the statistical significance of coefficients was evaluated using t -tests. A significance threshold of $p < 0.05$ was applied.

3.8.4 Analysis of Variance (ANOVA)

A two-way ANOVA was conducted to test whether importance ratings differed significantly according to skill type and participant. This allowed for the simultaneous examination of differences in how technical skills were valued, while also accounting for variation in individual scoring tendencies among coaches.

The dependent variable was the expert importance rating (Likert scale 1–5). The two fixed factors entered into the model were:

- Skill type (six levels: (aerial duel (won), chance created, defensive duel (won), dribble (successful), progressive pass (successful), and shot (goal)).
- Participant (seven experts providing the ratings)

The model can be expressed as:

$$Y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$$

Where:

- Y_{ij} = importance rating for skill i by participant j
- μ = overall mean rating
- α_i = effect of skill type i
- β_j = effect of participant j
- ϵ_{ij} = residual error

The null hypothesis for each factor was that mean ratings did not differ across its levels. The F-statistic and associated p -values were used to assess statistical significance, with $p < 0.05$ considered significant.

3.9 Statistical Reporting

All analyses were conducted in R (version 4.5.1). Results were reported with descriptive statistics (means, standard deviations, standard errors) alongside inferential outcomes (p -values and regression coefficients). This ensured findings were both statistically rigorous and interpretable in a coaching context.

4.0 Results

This chapter presents the results of the study in 8 sections. Section 4.1 begins with a brief overview of the dataset and the structure of the data collected. Section 4.2 outlines the results from the expertise evaluation, detailing how performance variables were rated in importance by experienced coaches and analysts across six playing positions. Section 4.3 then examines variation in importance ratings by playing position, using selected representative variables to illustrate positional trends and applying Fisher's Exact Test to test whether positional differences were statistically significant. Section 4.4 analyses inter-rater deviation across participants to evaluate consistency in expert opinion and explores whether deviation was related to participant characteristics (age and years at the club). Section 4.5 presents results from the linear regression model assessing whether importance ratings differed by skill type. Section 4.6 reports the two-way ANOVA findings examining the effects of skill type and participant on importance ratings. Section 4.7 presents the final Game Performance Index (GPI) positional formulas derived from the expert weightings. Finally, Section 4.8 applies the GPI formulas to match performance data and presents the player rankings within each position group.

4.1 Dataset Overview

The dataset consisted of technical performance ratings and match data for 23 Rangers FC players from the U18 and B Team squads within the Professional Development Phase (PDP) across the 2023/24 season. Each player's performance was analysed across 30 matches using the professional analysis platforms Wyscout and Sportscore, with every on-ball and off-ball action coded. Technical performance variables were ratio-adjusted for playing time and then standardised by position by subtracting the positional mean from each player's value and dividing by the positional standard deviation, resulting in z-scores. In addition, coach evaluations of technical variable importance were collected using a five-point Likert scale and used to determine the weighting applied to each variable within the Game Performance Index (GPI) formula.

4.2 Expertise Evaluation

Seven expert coaches and analysts participated in the variable importance evaluation using a Likert scale ranging from 1 (Not Important) to 5 (Extremely Important). Variables were

grouped as either positive or negative actions, with positive actions referring to those that contribute to a successful match outcome (e.g., progressive pass (successful), shot (goal)), and negative actions referring to those that contribute to an unsuccessful outcome (e.g., errors leading to opposition chance, lateral pass (unsuccessful)). Results are summarised for six playing positions: Centre Back (CB), Full Back (FB), Defensive Midfielder (DM), Attacking Midfielder (AM), Winger (W), and Centre Forward (CF). Full positional expertise evaluation tables are provided in Appendix A Tables 1A–6A.

The table below displays the mean importance scores $\pm$ standard deviation (SD) for each variable by position. A higher mean indicates greater perceived importance assigned by coaches for that specific playing position, while the standard deviation reflects the level of variation in ratings between participants.

Table 4. Variable Importance Ratings (Mean $\pm$ SD) by Position

<i>Variable</i>	<i>Position</i>					
	CB	FB	DM	AM	W	CF
<i>Aerial duel (won)</i>	5.00 $\pm$ 0.00	4.14 $\pm$ 0.69	3.86 $\pm$ 0.69	2.57 $\pm$ 0.53	2.14 $\pm$ 0.90	3.86 $\pm$ 0.90
<i>Defensive duel (won)</i>	5.00 $\pm$ 0.00	5.00 $\pm$ 0.00	4.71 $\pm$ 0.49	3.43 $\pm$ 1.40	2.71 $\pm$ 1.25	2.86 $\pm$ 1.07
<i>Dribble (successful)</i>	2.86 $\pm$ 1.07	4.00 $\pm$ 0.82	3.29 $\pm$ 0.95	4.14 $\pm$ 0.69	5.00 $\pm$ 0.00	3.71 $\pm$ 0.95
<i>Interception (successful)</i>	4.86 $\pm$ 0.38	4.57 $\pm$ 0.53	4.71 $\pm$ 0.49	3.57 $\pm$ 0.79	2.71 $\pm$ 1.11	2.86 $\pm$ 1.35
<i>Offensive duel (successful)</i>	3.00 $\pm$ 1.15	3.71 $\pm$ 0.95	3.71 $\pm$ 0.76	4.29 $\pm$ 0.49	4.71 $\pm$ 0.49	4.00 $\pm$ 0.82
<i>Loose ball duel (successful)</i>	4.43 $\pm$ 0.53	4.00 $\pm$ 0.82	4.43 $\pm$ 0.53	3.57 $\pm$ 1.27	2.71 $\pm$ 1.11	2.14 $\pm$ 1.21
<i>Chance Created</i>	2.00 $\pm$ 1.53	4.14 $\pm$ 0.69	3.57 $\pm$ 0.79	4.71 $\pm$ 0.49	4.86 $\pm$ 0.38	4.00 $\pm$ 0.82
<i>Pass to final third (successful)</i>	3.29 $\pm$ 0.76	4.29 $\pm$ 0.76	4.86 $\pm$ 0.38	4.43 $\pm$ 1.27	3.71 $\pm$ 1.50	2.57 $\pm$ 0.98
<i>Pressing duel</i>	2.71 $\pm$ 1.11	3.14 $\pm$ 1.07	3.43 $\pm$ 1.13	3.57 $\pm$ 1.13	4.29 $\pm$ 1.50	4.29 $\pm$ 1.50
<i>Shot (on target)</i>	1.71 $\pm$ 0.76	2.43 $\pm$ 0.79	3.29 $\pm$ 0.49	4.29 $\pm$ 0.49	4.43 $\pm$ 0.53	5.00 $\pm$ 0.00
<i>Shot (goal)</i>	2.71 $\pm$ 1.70	2.86 $\pm$ 1.57	3.57 $\pm$ 0.98	4.57 $\pm$ 0.53	4.71 $\pm$ 0.49	5.00 $\pm$ 0.00

<i>Progressive pass (successful)</i>	4.86 ± 0.38	4.57 ± 0.53	4.86 ± 0.38	4.71 ± 0.76	3.43 ± 0.98	3.00 ± 1.00
<i>Lateral pass (successful)</i>	3.29 ± 0.95	3.43 ± 0.79	4.00 ± 0.82	3.43 ± 1.51	2.71 ± 0.95	2.71 ± 0.95
<i>Forward pass (successful)</i>	4.57 ± 0.79	4.71 ± 0.49	4.86 ± 0.38	4.86 ± 0.38	3.86 ± 1.07	3.14 ± 1.07
<i>Aerial duel (Lost)</i>	5.00 ± 0.00	4.14 ± 0.69	3.86 ± 0.69	2.57 ± 0.53	2.14 ± 0.90	4.00 ± 0.58
<i>Defensive duel (Lost)</i>	4.86 ± 0.38	4.86 ± 0.38	4.43 ± 0.53	3.00 ± 1.41	2.71 ± 1.25	2.57 ± 0.79
<i>Dribble (unsuccessful)</i>	3.57 ± 0.98	3.43 ± 0.53	3.43 ± 0.98	3.86 ± 0.90	4.57 ± 0.79	3.86 ± 0.69
<i>Fouls performed that originated dangerous situations</i>	5.00 ± 0.00	4.71 ± 0.49	4.71 ± 0.49	3.14 ± 1.07	2.71 ± 1.25	2.43 ± 1.51
<i>Interception (unsuccessful)</i>	4.71 ± 0.49	4.71 ± 0.49	4.43 ± 0.79	3.57 ± 1.13	2.29 ± 0.95	2.14 ± 0.90
<i>Offensive duel (unsuccessful)</i>	2.71 ± 1.50	3.29 ± 0.95	3.57 ± 1.40	4.29 ± 0.76	4.43 ± 0.79	4.00 ± 1.15
<i>Loose ball duel (unsuccessful)</i>	4.14 ± 0.69	3.86 ± 0.90	4.29 ± 1.38	3.71 ± 1.70	2.86 ± 1.21	2.86 ± 1.21
<i>Pass to final third (unsuccessful)</i>	3.14 ± 1.07	3.43 ± 1.40	4.57 ± 0.98	4.29 ± 1.11	4.00 ± 1.00	2.43 ± 1.51
<i>Shot (off target)</i>	1.43 ± 0.53	2.14 ± 0.90	2.86 ± 0.69	4.00 ± 0.82	4.14 ± 1.07	4.86 ± 0.38
<i>Shot (blocked)</i>	1.43 ± 0.53	2.14 ± 0.90	2.86 ± 0.69	3.86 ± 0.69	4.14 ± 0.69	4.86 ± 0.38
<i>Progressive pass (unsuccessful)</i>	4.71 ± 0.49	4.29 ± 0.76	4.86 ± 0.38	4.71 ± 0.49	3.71 ± 0.95	3.29 ± 1.38
<i>Lateral pass (unsuccessful)</i>	3.71 ± 0.95	3.43 ± 0.98	4.00 ± 1.15	3.43 ± 1.51	2.86 ± 0.90	2.57 ± 0.98
<i>Forward pass (unsuccessful)</i>	4.43 ± 0.79	4.14 ± 1.21	4.86 ± 0.38	4.57 ± 0.98	3.71 ± 0.95	3.29 ± 1.11

<i>Error leading to opposition chance</i>	5.00 ± 0.00	5.00 ± 0.00	4.43 ± 1.51	3.71 ± 1.70	3.29 ± 1.25	3.29 ± 1.25
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Defensive attributes such as aerial duel (won), defensive duel (won), and interception (successful) were rated highest for central defenders (CB), with mean values close to the maximum (5.0 ± 0.44). Full backs (FB) and Defensive midfielders (DM) also received relatively high ratings for these defensive variables, although consistently lower than CBs. Conversely, attacking players, particularly attacking midfielders (AM), wingers (W), and centre forwards (CF), were assigned much lower importance for these defensive metrics.

Clear positional differences were observed, reflecting the distinct tactical and technical demands associated with each role. In contrast, attacking contributions such as chances created, shots on target, and goals scored were most highly valued for advanced positions. Wingers and attacking midfielders were rated strongly for chance creation (4.86 ± 0.35 and 4.71 ± 0.25 , respectively), while centre forwards were rated highest for both shot accuracy and goal scoring (5.0 ± 0.35). Similarly, successful dribbles were considered of greatest importance for wingers (5.0 ± 0.35), but much less relevant for defenders.

Passing-related variables revealed a more distributed pattern. Progressive and forward passes were considered highly important for defensive midfielders (both 4.86 ± 0.24) and attacking midfielders (4.71 – 4.86 ± 0.25), reflecting their transitional and creative responsibilities. Centre backs and full backs were also rated highly for progressive passing, suggesting experts viewed them as key contributors to build-up play. In contrast, lateral passing was consistently rated lower across all positions, particularly in advanced attacking roles.

Negative outcome variables (e.g., aerial duel (lost), defensive duel (lost), errors leading to opposition chance) were consistently rated as highly important to avoid in defensive positions, particularly for CBs and FBs, where scores approached the maximum ($\geq 4.8 \pm 0.44$). For attacking players, these variables were rated lower, reflecting a reduced emphasis on defensive errors in their roles.

Overall, the data highlights a clear divergence in the technical performance priorities of experts depending on positional context. Defensive solidity dominated the evaluation of

centre backs and full backs, while creativity, chance creation, and goal-scoring variables were most valued for attacking midfielders, wingers, and centre forwards. Defensive midfielders were characterised by a balance of defensive contribution and passing progression, situating them between defensive and attacking profiles

4.3 Variation in Importance Ratings by Playing Position

To examine whether different playing positions value certain technical actions more than others, participants rated the importance of performance metrics using a 5-point Likert scale. From the wider dataset, six representative variables were selected for focused analysis: Aerial duel (won), chance created, defensive duel (won), Shot (Goal), dribble (Successful), and progressive pass (successful). These variables were chosen to capture a balance of attacking and defensive actions.

Clear positional trends were evident. Aerial duel (won) and defensive duel (won) were rated highest for centre backs (both 5.0 ± 0.44), with full backs and defensive midfielders also valued strongly, but much lower ratings were recorded for attacking roles. In contrast, chance created and shot (goal) were considered most important for attacking midfielders, wingers, and centre forwards, with CFs recording the maximum score for goal scoring (5.0 ± 0.35). Dribble (successful) was rated highest for wingers (5.0 ± 0.35), reflecting their reliance on 1v1 ability, but were of least importance to CBs (2.86 ± 0.44). Finally, progressive pass (successful) was rated most important for defensive midfielders (4.86 ± 0.24) and attacking midfielders (4.71 ± 0.25), underlining their central role in advancing possession.

Taken together, these findings highlight distinct positional priorities: defensive dominance for centre backs and full backs, progression and distribution for defensive midfielders, and creativity, dribbling, and goal involvement for attacking midfielders, wingers, and centre forwards. While observable differences in the data suggest clear patterns, the Fisher's Exact Test was applied to formally assess whether these positional differences in skill importance were statistically significant. This test was chosen due to its suitability for small sample sizes and categorical data, ensuring a rigorous evaluation of the consistency of these positional trends across the cohort.

Table 5.. Distribution of Likert scale ratings for Aerial Duel (won) across playing positions.

Aerial Duel (won)

<i>Position</i>	Likert Scale (1 to 5)				
	1	2	3	4	5
<i>CB</i>	0	0	0	0	7
<i>FB</i>	0	0	1	4	2
<i>DM</i>	0	0	2	4	1
<i>AM</i>	0	3	4	0	0
<i>W</i>	2	2	3	0	0
<i>CF</i>	0	0	3	2	2

Table 6. Distribution of Likert scale rating for Chance Created across playing positions.

Chance Created

<i>Position</i>	Likert Scale (1 to 5)				
	1	2	3	4	5
<i>CB</i>	3	3	0	0	1
<i>FB</i>	0	0	1	4	2
<i>DM</i>	0	0	4	2	1
<i>AM</i>	0	0	0	2	5
<i>W</i>	0	0	0	1	6
<i>CF</i>	1	1	2	2	1

Table 7. Distribution of Likert scale ratings for *Defensive Duel (won)* across playing positions.

Defensive Duel (won)

<i>Position</i>	Likert Scale (1 to 5)				
	1	2	3	4	5
<i>CB</i>	0	0	0	0	7
<i>FB</i>	0	0	0	0	7
<i>DM</i>	0	0	0	2	5
<i>AM</i>	0	1	4	0	2
<i>W</i>	1	2	3	0	1
<i>CF</i>	0	3	3	0	1

Table 8. Distribution of Likert scale ratings for *Dribble (successful)* across playing positions.

Dribble (successful)

<i>Position</i>	Likert Scale (1 to 5)				
	1	2	3	4	5
<i>CB</i>	0	3	3	0	1
<i>FB</i>	0	0	2	3	2
<i>DM</i>	0	1	4	1	1
<i>AM</i>	0	0	1	4	2
<i>W</i>	0	0	0	0	7
<i>CF</i>	0	1	1	4	1

Table 9. Distribution of Likert scale ratings for *Progressive Pass (successful)* across playing positions.

Progressive Pass (successful)

<i>Position</i>	Likert Scale (1 to 5)				
	1	2	3	4	5
<i>CB</i>	0	0	0	1	6
<i>FB</i>	0	0	0	3	4
<i>DM</i>	0	0	0	1	6
<i>AM</i>	0	0	1	0	6
<i>W</i>	0	1	3	2	1
<i>CF</i>	0	2	4	0	1

Table 10. Distribution of Likert scale ratings for Shot (goal) across playing positions.

Shot (goal)

<i>Position</i>	Likert Scale (1 to 5)				
	1	2	3	4	5
<i>CB</i>	2	2	1	0	2
<i>FB</i>	1	3	1	0	2
<i>DM</i>	0	0	5	2	0
<i>AM</i>	0	0	0	3	4
<i>W</i>	0	0	0	2	5
<i>CF</i>	0	0	0	0	7

Table 11. P-values from Fisher’s Exact Tests examining the association between playing position and importance ratings for each technical variable.

<i>Variable</i>	<i>P-Value</i>
<i>Aerial duel (won)</i>	<0.001
<i>Chance Created</i>	<0.001
<i>Defensive duel (won)</i>	<0.001
<i>Dribble (successful)</i>	<0.01
<i>Progressive pass (successful)</i>	<0.01
<i>Shot (goal)</i>	<0.001

Table 11 revealed that all six tested technical performance variables demonstrated statistically significant differences across playing positions. Specifically, aerial duel (won), defensive duel (won), chance created and shot (goal) all returned p-values < 0.001, while progressive pass (successful) and dribble (successful) returned p-values < 0.01. As all values fell below the conventional $p < 0.05$ threshold, the null hypothesis of no positional difference was rejected in each case. These results confirm that these performance metrics were not rated uniformly across the cohort, highlighting their discriminative value in differentiating technical expectations by position.

4.4 Participant Deviation Analysis

To assess the consistency of participant responses in rating technical performance metrics, each coach’s average deviation score was calculated. This score indicates how closely a participant’s ratings aligned with the average ratings for their assigned position across all 28 variables. Specifically, for each coach, the absolute difference between their rating and the group mean was calculated for every variable–position combination (28 variables $\times$ 6 positions), then averaged across all values to generate a single deviation score. The lower the deviation score, the more closely a participant’s responses aligned with the positional consensus across the full dataset.

The following scatter plots explore whether these deviation scores were influenced by participant characteristics, specifically age and years at the club.

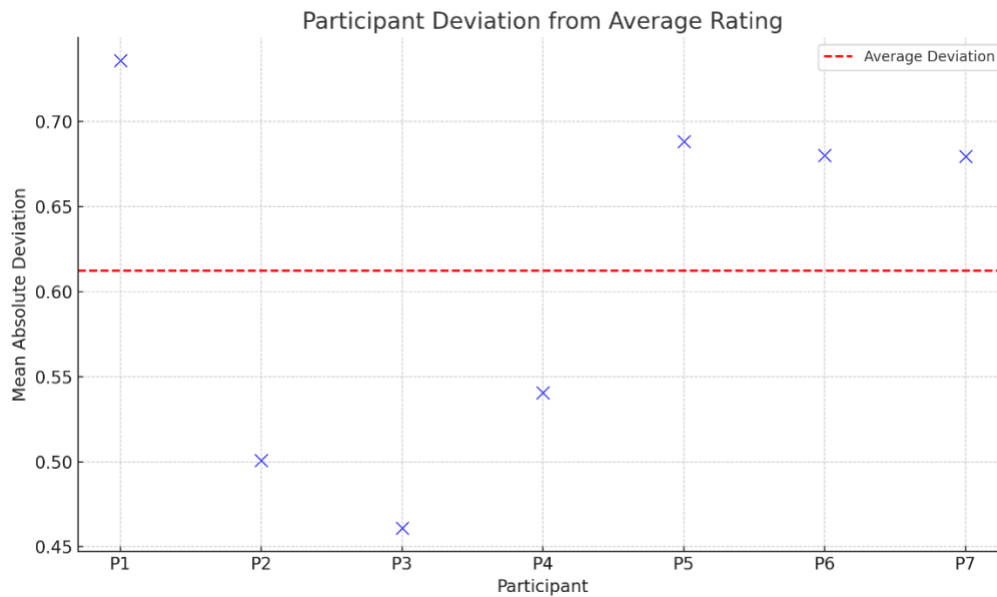


Figure 2. Scatter plot of overall participant deviation in importance ratings.

The first plot displays the overall spread of average deviation scores across all participants. There is a wide distribution of scores, suggesting varying levels of agreement with positional norms among the sample. Some participants showed a high degree of alignment, while others deviated more substantially. No grouping or correlation analysis was applied at this stage, but this visual contextualises the variation prior to subgroup analysis.

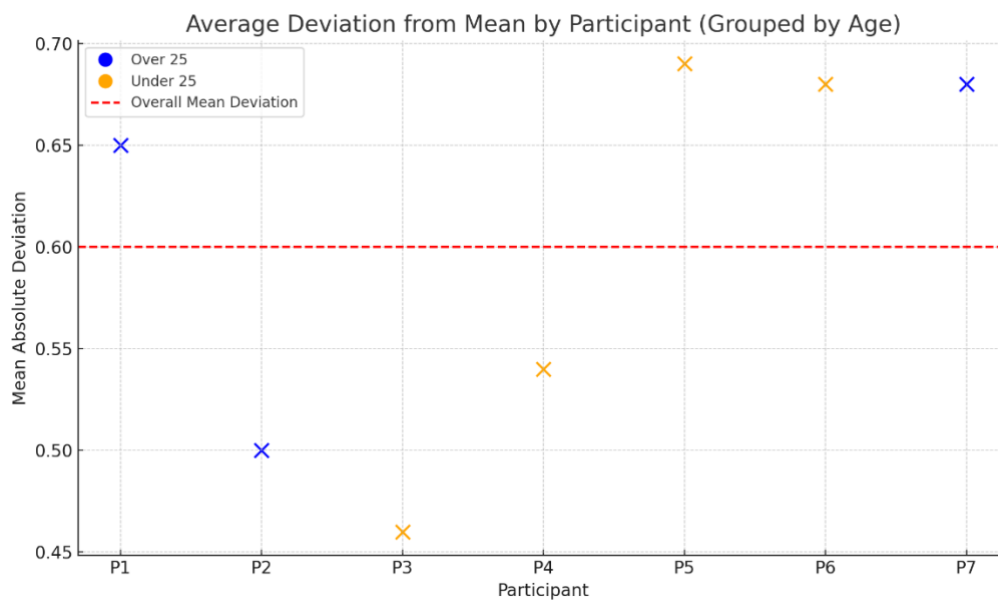


Figure 3. Scatter plot of participant deviation in importance ratings, split by participants age (over and under 25 years old.)

The second plot examines whether participant age group (under 25 vs. over 25) was associated with the level of deviation. A very weak positive correlation was found ($r = 0.231$, $p = 0.618$), indicating no statistically significant relationship. This suggests that older or younger participants were not systematically more or less aligned with the group norm.

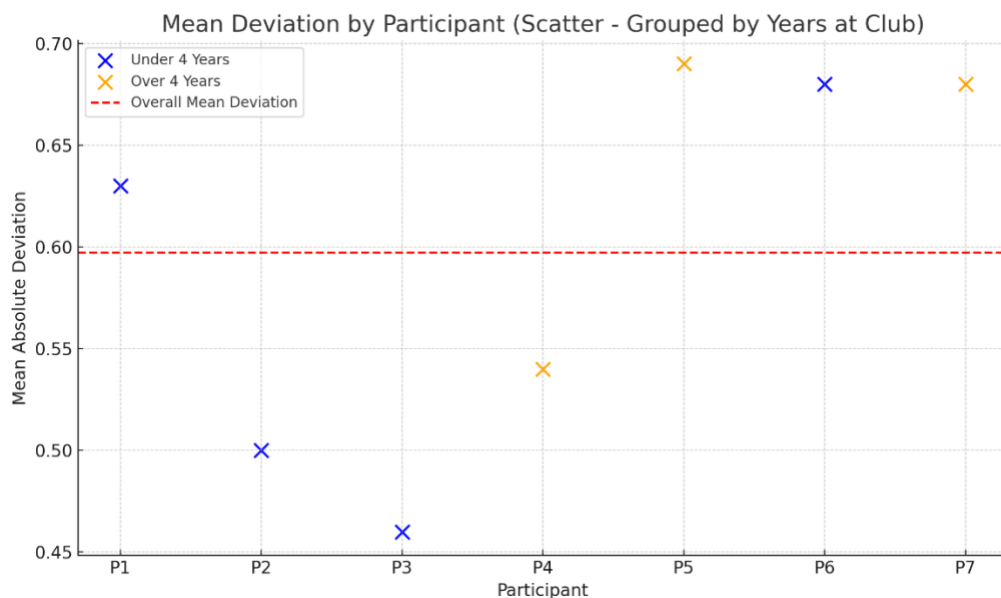


Figure 4. Scatter plot of participant deviation in importance ratings, split by years at the club (over vs. under 4 years)

The final plot investigates the relationship between participant length of service at the club (grouped as under 4 years vs. 4 years or more) and deviation scores. Again, the correlation was very weak and not significant ($r = 0.203$, $p = 0.663$), implying that length of service at the club did not substantially influence agreement with positional expectations.

Overall, this pattern indicates that variation in expert ratings was systematic rather than random, reflecting differences in individual coaching emphasis rather than inconsistency or misunderstanding of the task.

4.5 Differences in Importance Ratings by Skill Type: Regression Modelling

Linear Regression Model: Skill as Predictor

A linear regression model was conducted to test whether skill type significantly predicted importance ratings (reference category: *Aerial duel (won)*)

Table 12. Linear Regression Predicting Importance Ratings by Skill Type

Predictor	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.5952	0.1831	19.64	< 0.001**
Chance created	0.2857	0.2589	1.10	0.271
Defensive duel (won)	0.3571	0.2589	1.38	0.169
Dribble (successful)	0.2381	0.2589	0.92	0.359
Progressive pass (successful)	0.6243	0.2605	2.40	<0.05*
Shot (goal)	0.3095	0.2589	1.20	0.233

Predictor = variable included in the regression model; **Estimate** = unstandardised regression coefficient; **Std. Error** = standard error of the estimate; **t value** = test statistic for the coefficient; **Pr(>|t|)** = probability (*p*-value) that the coefficient differs from zero.

Table 13. Model fit statistics for the linear regression predicting importance ratings by skill type.

<i>Model Statistic</i>	<i>Value</i>
<i>Residual Std. Error</i>	1.186
<i>Multiple R-squared</i>	0.0238
<i>Adjusted R-squared</i>	0.0039
<i>F-statistic (5, 245)</i>	1.194
<i>Model p-value</i>	0.3129

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The regression analysis confirmed that progressive pass (successful) was rated significantly higher than aerial duel (won) ($p < 0.05$). No other skill types demonstrated statistically significant differences. The overall model was not significant ($p = 0.3129$), suggesting that, although progressive passing emerged as a notable outlier, skill type alone explained only a small proportion of the variance in importance ratings. These findings indicate that the six technical skills were largely considered consistently important by coaches, with minimal variation in ratings when averaged across the dataset. These findings indicate that skill type alone provides limited explanatory power for importance ratings.

4.6 Coach and Skill Effects: ANOVA

To investigate whether individual participants differed in how they rated the importance of technical skills, a two-way ANOVA was conducted with skill and participant entered as fixed factors.

Table 14. ANOVA - Effect of Skill and Participant on Importance Ratings

<i>Source</i>	<i>Df</i>	<i>Sum Sq</i>	<i>Mean Sq</i>	<i>F value</i>	<i>Pr(>F)</i>
<i>Skill</i>	5	9.02	1.80	1.32	0.255
<i>Participant</i>	6	18.16	3.03	2.22	< 0.05 *
<i>Residuals</i>	240	327.34	1.36		

Source = factor or error term in the model; Df = degrees of freedom; Sum Sq = sum of squares (variation explained); Mean Sq = mean squares (sum of squares ÷ df); F value = F-statistic for the effect; Pr(>F) = probability (*p*-value) of obtaining the observed F under the null hypothesis.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The ANOVA assessed the effects of both skill type and participant on importance ratings. For skill type, the model allocated 5 degrees of freedom, with a sum of squares of 9.02 and a mean square of 1.80. This resulted in an F value of 1.32 and a non-significant $p = 0.255$, indicating that variation in importance ratings was not systematically explained by differences between the six skill categories. By contrast, participant accounted for a larger proportion of variance, with 6 degrees of freedom, a sum of squares of 18.16, and a mean square of 3.03. The corresponding F value of 2.22 reached statistical significance ($p < 0.05^*$), showing that coaches differed systematically in their overall ratings. The residuals (240 df) captured the majority of variance (sum of squares = 327.34, mean square = 1.36), highlighting that a substantial proportion of variation remained unexplained by the model.

Overall, the ANOVA identified a statistically significant main effect of participant and a non-significant main effect of skill type on importance rating

4.7 Application of the GPI Formula

The position-specific Game Performance Index (GPI) formulas were applied to match performance data collected from Rangers FC Professional Development Phase (PDP) players during the 2023/24 season. Each player's technical performance data was standardised and applied to the formula corresponding to the position performed within each match, generating composite scores based on the expert-derived variable weightings. The complete position-specific GPI formulas used within this process are presented in Appendix B.

Table 15 – Rangers FC PDP Academy Centre Backs 23/24 ranking using the GPI formula.

RANK	1	2	3	4
PLAYER ID	CB2	CB1	CB4	CB3
GPI GRADE	0.048	-0.060	-0.071	-0.110
AD (L)	0.446	0.058	-0.359	0.446
AD (W)	-0.016	0.824	-0.352	0.362
DD (L)	0.120	-0.319	0.976	1.369
DD (W)	0.450	-0.354	-0.212	0.603
I (S)	0.722	-1.037	-0.421	0.458
I (U)	0.366	-0.597	0.302	-0.212
LBD (L)	-0.377	2.082	-0.608	-0.147
LBD (W)	0.447	-0.297	-0.552	0.611
DRI (U)	-0.165	-0.100	-0.100	0.226
ELOC	0.229	0.161	0.637	0.024
FPODS	0.334	-0.626	-0.626	0.654
LAT (S)	-0.423	0.652	-0.544	-0.847
LAT (U)	-0.311	-0.010	-0.643	1.136
FOR (S)	0.339	-0.448	-0.832	0.266
FOR (U)	0.548	-0.126	-0.941	0.823
PRO (S)	1.262	-0.809	-0.930	0.870
PRO (U)	0.519	-0.698	-0.698	0.932
F3 (S)	0.096	-0.129	-0.493	0.668
F3 (U)	0.261	-0.175	-0.731	0.261

Player ID : specific ID given to every player, GPI Grade : Game Performance Index Grade, AD (L) : Aerial duel – Lost, AD (W) : Aerial duel – won, DD (L) : Defensive duel – Lost, DD (W) : Defensive duel – won, I (S) : Interception – Successful, I (U) : Interception – Unsuccessful, LBD (L) : Loose Ball duel – Lost, LBD (W) : Loose Ball duel – won, DRI (U) : Dribble – Unsuccessful, ELOC : Error Leading to Opposition Chance, FPODS : Fouls performed that originated dangerous situations, LAT (S) : Lateral Pass – Successful, LAT (U) : Lateral Pass – Unsuccessful, FOR (S) : Forward Pass – Successful, FOR (U) : Forward Pass – Unsuccessful, PRO (S) : Progressive Pass – Successful, PRO (U) : Progressive Pass – Unsuccessful, F3 (S) : Pass to Final Third – Successful, F3 (U) : Pass to Final Third – Unsuccessful

Table 16 – Rangers FC PDP Academy Full Backs 23/24 ranking using the GPI formula

<i>RANK</i>	1	2	3	4
PLAYER ID	FB4	FB1	FB3	FB2
GPI GRADE	0.103	0.012	-0.129	-0.152
AD (L)	0.258	-0.616	0.186	0.017
AD (W)	-0.235	-0.919	0.098	0.584
DD (L)	-0.600	-0.909	0.811	0.374
DD (W)	0.235	-0.717	0.048	-0.717
OD (L)	0.623	-0.278	-0.567	-0.567
OD (W)	0.810	-0.342	-0.342	-0.342
I (S)	1.605	-0.774	-0.493	-0.720
I (U)	0.199	-0.135	-0.689	-0.412
LBD (L)	-0.153	-0.101	-0.609	0.915
LBD (W)	0.367	-0.760	-0.681	-0.069
DRI (S)	-0.321	-0.398	-0.482	0.125
DRI (U)	0.882	-1.037	-0.316	-0.135
ELOC	-0.193	-0.215	-0.215	-0.215
CC	-1.506	0.175	0.426	0.488
FPODS	0.025	-0.593	0.838	0.003
LAT (S)	0.209	-0.137	-0.773	-0.264
LAT (U)	-0.308	-0.594	0.057	0.276
FOR (S)	0.619	-0.553	-1.069	-0.077
FOR (U)	0.149	-0.399	-0.956	0.490
PRO (S)	-0.048	-0.648	0.258	-0.168
PRO (U)	0.164	-0.481	-0.075	0.280
F3 (S)	-0.423	0.695	-0.189	0.355
F3 (U)	-0.791	-0.240	-0.266	0.773

Player ID : specific ID given to every player, GPI Grade : Game Performance Index Grade, AD (L) : Aerial duel – Lost, AD (W) : Aerial duel – won, DD (L) : Defensive duel – Lost, DD (W) : Defensive duel – won, OD (L) : Offensive duel - Lost , OD (W) : Offensive duel – won, I (S) : Interception – Successful, I (U) : Interception – Unsuccessful, LBD (L) : Loose Ball duel – Lost, LBD (W) : Loose Ball duel – won, DRI (S) : Dribble – Successful, DRI (U) : Dribble – Unsuccessful, ELOC : Error Leading to Opposition Chance, CC: Chance Created, FPODS : Fouls performed that originated dangerous situations, LAT (S) : Lateral Pass – Successful, LAT (U) : Lateral Pass – Unsuccessful, FOR (S) : Forward Pass – Successful, FOR (U) : Forward Pass – Unsuccessful, PRO (S) : Progressive Pass – Successful, PRO (U) : Progressive Pass – Unsuccessful, F3 (S) : Pass to Final Third – Successful, F3 (U) : Pass to Final Third – Unsuccessful

Table 17 – Rangers FC PDP Academy Defensive Midfielder 23/24 ranking using the GPI formula

RANK	1	2	3
PLAYER ID	DM3	DM1	DM2
GPI GRADE	0.062	0.028	-0.003
AD (L)	-0.110	-0.260	-0.110
AD (W)	-0.713	-0.412	0.665
DD (L)	-0.047	-0.709	0.218
DD (W)	-0.412	-0.903	1.390
OD (L)	-0.156	-0.490	1.477
I (S)	0.710	-0.718	0.248
I (U)	0.907	-0.391	-0.054
LBD (L)	-0.101	-0.442	0.077
LBD (W)	0.395	-0.610	1.085
PD	0.885	-0.681	0.047
DRI (S)	-0.717	-0.185	1.188
DRI (U)	-0.656	0.061	0.923
SHO (G)	-0.277	0.582	-0.277
SHO (ON)	0.022	0.459	-0.321
ELOC	-0.272	-0.272	0.353
CC	-0.510	0.423	-0.168
FPODS	-0.027	-0.234	-0.481
LAT (S)	-0.286	0.353	-0.612
LAT (U)	-0.858	0.317	1.358
FOR (S)	0.548	0.399	-0.193
FOR (U)	-0.133	0.024	0.854
PRO (S)	0.506	-0.213	-0.276
PRO (U)	0.062	-0.146	0.062
F3 (S)	-0.415	0.410	0.846

Player ID : specific ID given to every player, GPI Grade : Game Performance Index Grade, AD (L) : Aerial duel – Lost, AD (W) : Aerial duel – won, DD (L) : Defensive duel – Lost, DD (W) : Defensive duel – won, OD (L) : Offensive duel - Lost , I (S) : Interception – Successful, I (U) : Interception – Unsuccessful, LBD (L) : Loose Ball duel – Lost, LBD (W) : Loose Ball duel – won, PD : Pressing duel, DRI (S) : Dribble – Successful, DRI (U) : Dribble – Unsuccessful, SHO (G) : Shot – Goal, SHO (ON) : Shot – On Target, ELOC : Error Leading to Opposition Chance, CC: Chance Created, FPODS : Fouls performed that originated dangerous situations, LAT (S) : Lateral Pass – Successful, LAT (U) : Lateral Pass – Unsuccessful, FOR (S) : Forward Pass – Successful, FOR (U) : Forward Pass – Unsuccessful, PRO (S) : Progressive Pass – Successful, PRO (U) : Progressive Pass – Unsuccessful, F3 (S) : Pass to Final Third – Successful, F3 (U) : Pass to Final Third - Unsuccessful

Table 18 – Rangers FC PDP Academy Attacking Midfielder 23/24 ranking using the GPI formula

<i>RANK</i>	1	2	3	4	5	6
PLAYER ID	AM1	AM4	AM3	AM5	AM6	AM2
GPI GRADE	0.1535	0.1289	0.0613	0.0082	-0.1207	-0.1554
DD (W)	2.0593	-0.0195	0.6967	-0.5864	-0.3668	-0.8417
OD (L)	0.1951	-0.9025	1.3462	-1.0230	-0.5555	1.6317
OD (W)	1.6523	-0.4187	1.1185	-0.5895	-0.0411	1.0047
I (S)	1.2243	-0.3030	-0.3030	-0.8584	-0.4935	-0.6732
I (U)	0.5066	-0.5485	0.2750	-0.0338	-0.7223	-0.5142
LBD (W)	0.3962	-0.0222	0.8146	-0.3360	-0.4617	-0.5800
PD	-0.0272	-0.9658	0.1719	-0.5960	0.6498	-0.0557
DRI (S)	-0.6356	1.7114	0.3582	-0.1916	0.3928	-0.6849
DRI (U)	-0.3908	-0.2605	0.9113	-0.3908	0.3628	-1.1503
SHO (B)	0.0179	0.7032	0.1261	-0.2346	-0.7116	1.6170
SHO (G)	-0.4966	-0.0416	1.5765	0.2112	-0.7868	0.5652
SHO (ON)	-0.1857	-0.5450	1.8502	-0.1857	-0.2389	0.0937
SHO (OFF)	-0.1649	-0.5499	-0.2076	-0.1649	0.3735	0.9332
CC	0.6636	0.0349	0.0349	0.2968	-0.1188	0.6636
FPODS	-0.3151	-0.2623	0.1594	0.0539	0.9785	-0.6841
LAT (U)	0.0639	-0.5391	0.0767	-0.2055	0.0824	-0.1457
FOR (S)	0.4828	1.1732	-0.3019	-0.2376	-0.8292	-0.7079
FOR (U)	0.7705	0.0569	0.3135	-0.2958	-0.3152	0.1532
PRO (S)	0.3478	0.4535	-1.0261	0.6252	-0.1809	-0.3920
PRO (U)	0.4036	0.8408	-0.6581	0.4036	0.4511	0.2579
F3 (S)	0.1412	0.3843	-0.1461	0.4507	-0.4859	0.5022

Player ID : specific ID given to every player, GPI Grade : Game Performance Index Grade, DD (W) : Defensive duel – won, OD (L) : Offensive duel - Lost , OD (W) : Offensive duel – won, I (S) : Interception – Successful, I (U) : Interception – Unsuccessful, LBD (W) : Loose Ball duel – won, PD : Pressing duel, DRI (S) : Dribble – Successful, DRI (U) : Dribble – Unsuccessful, SHO (B) : Shot – Blocked, SHO (G) : Shot – Goal, SHO (ON) : Shot – On Target, SHO (OFF) : Shot – Off Target, CC: Chance Created, FPODS : Fouls performed that originated dangerous situations, LAT (U) : Lateral Pass – Unsuccessful, FOR (S) : Forward Pass – Successful, FOR (U) : Forward Pass – Unsuccessful, PRO (S) : Progressive Pass – Successful, PRO (U) : Progressive Pass – Unsuccessful, F3 (S) : Pass to Final Third – Successful, F3 (U) : Pass to Final Third - Unsuccessful

Table 19 – Rangers FC PDP Academy Winger 23/24 ranking using the GPI formula

RANK	1	2	3	4
PLAYER ID	W4	W1	W3	W2
GPI GRADE	0.1375	0.0865	0.0601	-0.1518
OD (L)	-0.0746	0.8201	-0.9167	-0.7588
OD (W)	0.7037	0.5495	-0.8382	-0.8382
PD	-0.1671	1.0806	-0.8845	-0.0423
DRI (S)	1.1752	-0.3356	1.1265	-1.3590
DRI (U)	0.8315	0.0353	-0.5076	-0.0733
SHO (B)	-0.2388	0.0061	-0.7286	0.7408
SHO (G)	0.0045	0.4888	1.9418	-0.2377
SHO (ON)	-0.2311	1.0312	-0.3889	0.0845
SHO (OFF)	0.0654	0.7824	0.7824	0.4239
CC	-0.8143	0.8436	-1.1459	-1.1459
FOR (S)	-0.9143	1.3846	-0.3536	-1.3068
FOR (U)	-1.4569	0.7520	-0.4237	-1.8132
PRO (S)	0.3008	-0.3954	-0.0473	-0.7435
PRO (U)	-1.4256	0.7300	0.7300	-0.7070

Player ID : specific ID given to every player, GPI Grade : Game Performance Index Grade, OD (L) : Offensive duel - Lost , OD (W) : Offensive duel – won, Pressing duel, DRI (S) : Dribble – Successful, DRI (U) : Dribble – Unsuccessful, SHO (B) : Shot – Blocked, SHO (G) : Shot – Goal, SHO (ON) : Shot – On Target, SHO (OFF) : Shot – Off Target, CC: Chance Created, FOR (S) : Forward Pass – Successful, FOR (U) : Forward Pass – Unsuccessful, PRO (S) : Progressive Pass – Successful, PRO (U) : Progressive Pass – Unsuccessful, F3 (U) : Pass to Final Third – Unsuccessful

Table 20 – Rangers FC PDP Academy Centre Forward 23/24 ranking using the GPI formula

<i>RANK</i>	1	2	3
PLAYER ID	CF1	CF3	CF2
GPI GRADE	-0.0475	-0.0607	-0.2140
AD (L)	0.0610	0.1501	0.1501
AD (W)	-0.1650	0.6248	-0.7628
DD (W)	0.2011	0.2808	0.4103
PD	0.0232	-0.4251	-0.7465
DRI (S)	-0.5815	-0.6658	0.3231
DRI (U)	-0.6747	-0.3365	0.7149
SHO (B)	-0.6027	0.7693	-0.0414
SHO (G)	0.0981	-0.5271	-0.7529
SHO (ON)	-0.1973	-0.2612	-0.7281
SHO (OFF)	0.1997	-0.9023	0.7507

Player ID : specific ID given to every player, GPI Grade : Game Performance Index Grade, AD (L) : Aerial duel – Lost, AD (W) : Aerial duel – won, DD(W) : Defensive duel, Pressing duel, DRI (S) : Dribble – Successful, DRI (U) : Dribble – Unsuccessful, SHO (B) : Shot – Blocked, SHO (G) : Shot – Goal, SHO (ON) : Shot – On Target, SHO (OFF) : Shot – Off Target, CC: Chance Created

5.0 Discussion

The present study had two primary aims. Firstly, it sought to identify which technical performance metrics football coaches consider most important for each playing position. Secondly, it examined how these opinions differ between individual coaches, and how they align or contrast with existing literature and widely held views of the game. Although a new model, the Game Performance Index (GPI), was produced as part of the study, limitations in validation and clarity mean it is presented as a conceptual tool rather than a definitive measure. The primary contribution of this research is therefore the analysis of coaches' opinions, highlighting how perceived importance of technical metrics varies by position and skill type.

The discussion is structured around these aims. It begins by interpreting the positional patterns revealed by the expertise evaluation and the focused analysis of six representative variables. The statistical findings are then discussed in sequence, beginning with Fisher's Exact Tests, followed by the deviation analysis, regression modelling, and ANOVA. The chapter concludes by considering the applied implications of the GPI for academy practice.

5.1 Positional Profiles from the Expertise Evaluation

Coaches rated a comprehensive set of technical variables for each outfield position. These ratings underpinned the weighting tables for the position-specific GPI formulas and the inclusion thresholds reported in the results. Across the full set of variables, clear positional profiles emerged. Defenders prioritised duel success, both aerial and ground, as well as interceptive actions; midfielders emphasised progression and connection; while advanced roles placed greater importance on chance creation, dribbling, and finishing. This pattern aligns with established positional KPI frameworks and notational analysis principles that stress role-specific interpretation (Hughes et al., 2012; Sarmiento et al., 2018).

5.2 The Role of Negative Actions in Coach Evaluations

A notable constant across all positions was the emphasis placed on negative actions, particularly unsuccessful dribbles, which reached the inclusion threshold in every role. This reflects coaches' appreciation of risk–reward trade-offs. While successful dribbles can destabilise defensive structures, unsuccessful attempts often trigger dangerous transitions

(Sarmiento et al., 2020; Collet, 2013). The consistent inclusion of negative actions across positions supports the rationale for modelling both successful and unsuccessful contributions within the GPI framework, ensuring that performance evaluation captures not only positive impact but also the potential costs of technical failure.

5.3 Selection of Six Representative Positive Variables

Although negative variables were highly valued in the expertise evaluation, the six variables selected for detailed interpretation were all positive contributions. This was a deliberate decision, as these variables provided clearer positional contrasts and highlighted distinct technical demands across roles. Negative actions such as unsuccessful duels and dribbles showed relatively consistent importance across positions, whereas positive actions offered sharper differentiation between positions.

The six representative variables selected were aerial duel (won), defensive duel (won), progressive pass (successful), dribble (successful), chance created and shot (goal). These variables span defensive solidity, transitional play, and attacking output. Using a compact, representative set is consistent with prior research that illustrates positional contrasts through discriminant, high-leverage actions (Bradley et al., 2011; Mackenzie & Cushion, 2013), while the broader GPI model remained anchored in the full set of variables.

5.4 Positional Interpretation of the Six Key Variables

Clear positional differentiation emerged across the six representative variables. Aerial duel (won) and defensive duel (won) were maximised for centre backs, with full backs and defensive midfielders also rated highly, reflecting evidence that duel success discriminates elite defenders and reduces expected goals against (Yi et al., 2018; Modric et al., 2023). Progressive pass (successful) peaked for defensive and attacking midfielders, underlining their connective role in advancing possession and accessing dangerous zones (McHale & Relton, 2018).

Chance created was rated highest for attacking midfielders and wingers, while shot (goal) were maximised for centre forwards, reflecting the offensive responsibilities of advanced players in both creating and converting opportunities (Lago-Peñas et al., 2022). Dribble (successful) was rated most important for wingers, consistent with their role in destabilising

defensive blocks through 1v1 actions (Sarmiento et al., 2020). Collectively, these variables illustrate broader positional profiles in which defenders emphasise duels, midfielders emphasise progression, and attackers emphasise creativity and efficiency.

5.5 Positional Association of Variables: Fisher's Exact Tests

Fisher's Exact Tests confirmed that variable inclusion was significantly associated with playing position, indicating that the distribution of technical actions was not random but systematically structured according to positional role. Distinct positional clusters of variables were observed, reflecting coherent groupings of defensive, progression-based, and attacking actions.

Defensive actions, including aerial duel (won) and defensive duel (won), were predominantly associated with centre back and defensive midfield positions. In contrast, attacking actions such as shot (goal), chance created, and dribble (successful) were more frequently associated with winger and centre forward positions. Progression-based actions, most notably progressive pass (successful), were strongly associated with midfield roles, particularly attacking midfielders and defensive midfielders.

These patterns demonstrate that coaches conceptualise the importance of technical actions in a position-specific manner, with different actions considered salient depending on tactical role. This provides empirical support for the use of role-sensitive analytical approaches when examining technical performance, rather than relying on position-agnostic interpretations of match statistics (Hughes et al., 2012; Sarmiento et al., 2018).

5.6 Inter-Coach Variation: Deviation Analysis

The participant deviation analysis indicates that, although broad positional trends were evident at a group level, substantial individual differences existed in how coaches weighted technical actions. Some participants closely aligned with positional mean ratings, whereas others placed markedly greater or lesser emphasis on specific variables. This pattern highlights that expert-based performance evaluation in football is inherently shaped by individual interpretive frameworks and coaching philosophies, rather than representing a single unified model of importance. These deviation patterns were calculated across all

technical variables included in the study, rather than being limited to the six illustrative variables used for the other analysis.

Importantly, variation in deviation scores was not systematically associated with participant age or years at the club. Correlations between deviation magnitude and age (± 25 years: $r = 0.231$, $p = 0.618$) and between deviation magnitude and years at the club (± 4 years: $r = 0.203$, $p = 0.663$) were weak and non-significant, suggesting that differences in weighting behaviour were not explained by age or time served at the club. Instead, these findings suggest that individual views of performance are shaped by personal coaching background, playing experience, and tactical preferences.

Collectively, these results reinforce the notion that subjectivity is not a methodological flaw but a defining characteristic of applied performance evaluation. Rather than seeking a single “correct” set of variable weights, the present findings suggest value in modelling and visualising the range of expert perspectives. This supports the rationale for presenting the GPI as a flexible, coach-informed framework rather than a prescriptive or universally optimal metric. However, the small sample size necessitates caution, and future research involving larger and more diverse expert panels is required to further explore sources of variability in weighting behaviour.

5.7 Predictors of Variable Importance: Regression Modelling

Regression modelling provided further insight into predictors of importance ratings at the level of individual technical actions. The model intercept was 3.60 ($SE = 0.18$, $p < 0.001$), reflecting the baseline mean importance rating across variables. Of the skill predictors, only progressive pass (successful) reached statistical significance ($\beta = 0.624$, $SE = 0.260$, $p < 0.05$), indicating that coaches systematically rated progressive pass (successful) higher than the reference variable of aerial duel (won). Other variables, including dribbles (successful), chance created, and shot (goal), showed positive but non-significant coefficients, indicating limited explanatory power when skill type was considered in isolation.

Overall, the regression results suggest that individual technical actions are not uniformly differentiated in their perceived importance. Instead, only selected actions—most notably progressive passing—demonstrated systematic elevation relative to the reference category. This indicates that skill type alone explains only a small proportion of variance in importance

ratings, reinforcing the need to interpret technical actions within broader positional and contextual frameworks.

5.8 The Central Importance of Progressive Passing

The prominence of progressive passes within the regression model reinforces recent literature emphasising its importance in linking play and accessing dangerous areas. While defensive and attacking midfielders recorded the highest coefficients, the importance of progression extended across all positions. Full backs advance possession into the attacking third, centre backs initiate build-up through vertical passing, and forwards rely on progression to play the ball in threatening areas. This widespread applicability may explain why Progressive Pass (Successful) was the only variable to reach statistical significance, reflecting its role as a universal connector in modern tactical structures (McHale & Relton, 2018; Fernández-Navarro et al., 2016).

5.9 Coach and Skill Effects: ANOVA

A two-way analysis of variance (ANOVA) was conducted to examine whether expert importance ratings differed according to skill type and participant. This analysis was intended to assess overall rating tendencies across the selected technical actions while accounting for potential differences in how individual coaches applied the Likert scale.

A significant main effect of participant was observed, indicating systematic differences in overall rating tendencies between individual coaches. This suggests that, even when evaluating the same technical actions, experts differed in how strongly they expressed importance on the Likert scale. This effect reflects variation in scoring behaviour rather than disagreement about positional requirements, which were examined separately.

No strong overall effect of skill type was observed within the ANOVA framework, indicating that, when considered collectively, the selected technical actions were not rated as substantially different in average importance. Taken together, these findings indicate that differences in importance ratings were driven primarily by individual scoring tendencies rather than by uniform differences between skill categories. While coaches showed general agreement regarding which skills mattered most at a group level, they varied in how strictly or leniently they applied the rating scale (Mills et al., 2012; Larkin & O'Connor, 2017).

Importantly, the ANOVA examined broad patterns of rating behaviour and did not test positional differences or specific contrasts between individual skills. Positional variation in variable importance was assessed separately using Fisher's exact tests, while regression modelling was used to identify whether technical actions were rated higher than a reference category. The two analyses therefore address complementary, non-overlapping questions.

5.10 Applied Implications and the Role of the GPI

Although the primary focus of this research was to explore how coaches prioritise technical variables across positions, the development and application of the Game Performance Index (GPI) provided an interesting, applied outcome. The GPI operationalised expert-derived weightings into a position-specific index that integrated both positive and negative contributions. Unlike traditional indicators that reward volume without accounting for efficiency, the GPI penalised ineffective actions and rewarded efficiency in context, offering a more nuanced assessment of player performance (Collet, 2013).

When applied to the Rangers FC academy dataset, the GPI generated distinct positional profiles, demonstrating how coach-valued technical priorities translated into measurable match outcomes. This highlights the potential utility of the GPI as a developmental and evaluative tool within academy environments, while also reinforcing the need for further validation. The following sections examine these positional applications in greater detail.

5.10.1 Centre Backs

Among centre backs, CB2 recorded the highest GPI grade (0.048), ranking first within the positional group (Table 15). In contrast, CB3 recorded the lowest grade (-0.110). This spread illustrates the increasing importance of technical contribution in the modern centre back role, where involvement in possession and build-up play is now considered alongside traditional defensive actions. Recent match analysis data indicate that centre backs are increasingly involved in ball circulation and progression during the attacking phase, supporting evidence that distribution and build-up involvement are key components in evaluating central defenders (Praca et al., 2022; StatsPerform, 2023). The GPI reflected this shift by differentiating centre backs based on overall contribution rather than defensive output alone.

5.10.2 Full Backs

For full backs, the GPI highlighted the balance required between defensive solidity and attacking involvement. FB4 achieved the highest GPI grade (0.103), while FB2 recorded the lowest score (-0.152) (Table 16). This aligns with research emphasising the hybrid demands of the modern full back role, where players are required to contribute defensively in wide areas while also supporting attacking phases through overlaps and progression (Sampaio et al., 2021). The GPI framework reflected these expectations by rewarding full backs who demonstrated balanced contributions across both phases of play and penalising those who struggled to meet the dual demands of the position.

5.10.3 Defensive Midfielders

Among defensive midfielders, DM3 produced the highest GPI grade (0.062), whereas DM2 recorded the lowest grade (-0.003) (Table 17). These findings support the conceptualisation of the defensive midfielder as both a disruptor and a distributor, responsible for regaining possession and facilitating transitions into attack (Popovych, 2021). The GPI differentiated players within this positional group by capturing both defensive and possession-based contributions, reinforcing the importance of balanced performance in the defensive midfield role.

5.10.4 Attacking Midfielders

For attacking midfielders, the GPI demonstrated that modern expectations extend beyond creativity alone. AM1 achieved the highest GPI grade (0.1535), while AM2 recorded the lowest score (-0.1554) (Table 18). This supports research suggesting that attacking midfielders are increasingly required to contribute defensively through pressing and ball recovery, in addition to their creative responsibilities (Schulze, 2022). The GPI accounted for this two-way role by rewarding players who contributed across multiple phases of play and penalising those whose involvement was more limited.

5.10.5 Wingers

Among wingers, W4 achieved the highest GPI grade (0.1375), while W2 recorded the lowest score (-0.1518) (Table 19). This pattern reflects the central importance of 1v1 effectiveness in wide areas, where wingers are expected to destabilise defensive structures and create

attacking opportunities (Faude, 2019). The GPI mirrored this risk–reward dynamic by rewarding players whose overall contribution was positive and penalising those who underperformed relative to their positional demands.

5.10.6 Centre Forwards

For centre forwards, the GPI placed emphasis on both attacking output and defensive contribution. CF1 recorded the highest GPI grade (-0.0475) within the positional group, while CF2 recorded the lowest score (-0.2140) (Table 20). Although overall GPI values were lower for centre forwards compared to other positions, the model was still able to differentiate relative performance within the group. This supports existing literature suggesting that modern centre forwards are evaluated not only on goal scoring, but also on work rate, pressing, and overall contribution to team play (Saibene, 2022).

6.0 Limitations and Future Research

6.1 Limitations

Despite the conceptual and applied contributions of the present study, several important limitations must be acknowledged.

First, the expert panel was small and context specific. Only seven coaches and analysts participated, all drawn from a single elite academy environment (Rangers FC Professional Development Phase). This substantially limits the generalisability of the findings across different clubs, competitive levels, and footballing cultures. The positional importance weightings identified in this study should therefore be interpreted as context-bound rather than representative of wider coaching populations. Additionally, subgroup comparisons used within the participant deviation analysis (e.g., ≤ 4 years vs >4 years at the club) were exploratory and pragmatically derived to create broadly balanced group distributions within the small specialist sample, rather than representing definitive thresholds of expertise or professional competency.

Second, the study is inherently shaped by the subjective nature of coach judgement. Importance ratings reflect individual philosophies, experiences, and tactical preferences, which vary between practitioners. As a result, the findings do not represent objective truths about positional requirements but rather illustrate how performance is interpreted through professional judgement. Although participant deviation analysis was used to quantify variation between experts, subjectivity remains a fundamental constraint on the interpretability and transferability of the results.

Third, a limitation relates to the statistical approaches used to analyse expert ratings. While the present study applied separate statistical procedures to examine positional differences, participant variation, and variable importance individually, alternative approaches such as linear mixed-effects modelling may have allowed these relationships to be examined simultaneously within a single analytical framework. Mixed models would permit repeated ratings to be nested within participants while accounting for both fixed effects (e.g., position and variable type) and random effects (e.g., participant variation). However, the analytical structure adopted in the present study was intentionally designed to provide clearer step-by-step interpretation of each component of the dataset, supporting transparency and

interpretability within an exploratory applied football context. Given the relatively small specialist sample size, simpler statistical procedures were considered appropriate to avoid unnecessary model complexity while still identifying meaningful positional trends and patterns of expert agreement.

Fourth, the Game Performance Index (GPI) is not a validated performance metric. It was not tested against match outcomes, selection decisions, or external performance benchmarks, and no claims are made regarding its predictive accuracy or comparative superiority over existing commercial rating systems. The GPI is presented strictly as a conceptual and illustrative framework to demonstrate how coach-rated importance can be operationalised within a structured analytical model. Any interpretation beyond this purpose would be inappropriate.

Finally, match performance data were drawn exclusively from academy-level fixtures within a single club. Academy football differs from senior professional football in physical demands, tactical stability, and developmental priorities. Consequently, the application of the GPI and the interpretation of player scores are specific to a developmental context and should not be assumed to reflect performance evaluation at senior or elite professional levels.

6.2 Future Research

Building on the findings and limitations of the present study, several clear directions for future research emerge.

Future studies should seek to replicate the methodology across multiple clubs, competitive levels, and footballing cultures. Expanding the expert panel to include coaches from different academies, senior professional environments, and international contexts would allow researchers to examine whether positional importance profiles remain consistent or diverge across playing models and developmental philosophies. Comparative research between youth and senior coaches may be particularly valuable in understanding how performance expectations evolve across the player pathway.

Further research should also focus on the formal validation of the Game Performance Index framework. This could include examining relationships between GPI scores and external performance indicators such as coach selection decisions, match outcomes, longitudinal

player development, or progression to higher competitive levels. Such work would allow the GPI to move beyond a conceptual framework toward a validated evaluative tool, if supported by empirical evidence.

Longitudinal application of the GPI represents another important avenue for investigation. Applying position-specific formulas across multiple seasons would enable researchers to explore whether changes in player scores align with observed development trajectories, coaching feedback, and changes in role responsibility over time. This would be particularly relevant within academy settings, where long-term development rather than immediate performance is prioritised.

Future studies may also extend the framework beyond technical variables by integrating tactical, physical, and psychological dimensions of performance. Incorporating additional domains would support a more holistic representation of player contribution, reflecting the multidimensional nature of football performance and contemporary approaches to talent development.

Finally, complementary qualitative research could explore the underlying reasons behind coach importance ratings. Interviews or focus groups could examine how coaching philosophy, playing style, and developmental objectives influence the weighting of technical actions. This would deepen understanding of the decision-making processes that shape performance evaluation and further strengthen the link between applied coaching practice and analytical modelling

7.0 Conclusion

This study sought to explore which technical performance metrics football coaches consider most important across different playing positions and how these evaluations vary both within and between individuals. By engaging seven experienced coaches and analysts from Rangers FC, the research provided insight into how technical performance is valued within a defined professional academy context.

The findings illustrated clear positional patterns in perceived metric importance. Defensive actions such as aerial duels and defensive duels were prioritised for centre backs and defensive midfielders, while attacking contributions including chance creation, successful

dribbles, and shots (goal) were rated more highly for attacking midfielders, wingers, and centre forwards. These patterns highlight the importance of position-specific approaches to performance evaluation and reflect how the technical demands of each role shape coaching priorities. At the same time, systematic differences between individual participants highlighted the subjective nature of evaluation, with coaches differing in how strongly they expressed importance across the same set of actions.

When situated within the wider literature, the findings showed both areas of alignment and divergence. While existing research emphasises efficiency, passing networks, and tactical discipline as contributors to successful performance, coaches in this context placed greater emphasis on actions perceived to have direct positional impact. This reinforces the value of integrating practitioner insight alongside academic models when developing performance evaluation frameworks.

The Game Performance Index (GPI) was introduced in this study as a conceptual framework for visualising and operationalising coach-rated importance within a structured analytical model. It is not presented as a validated or predictive performance metric; rather, its application served to illustrate how expert judgement can be systematically embedded into position-specific grading approaches. As such, the GPI provides a foundation for future refinement, testing, and contextual comparison rather than a definitive evaluation tool.

Overall, this research contributes to a clearer understanding of how coaches value technical actions across playing positions within an academy environment. The findings emphasise the need for context-sensitive and role-specific approaches to performance evaluation and offer practical insight for coaching, scouting, and player development. Future research should seek to extend this work by incorporating larger and more diverse expert panels, validating coach-informed models against performance outcomes, and examining how positional priorities vary across competitive levels and tactical contexts.

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9.0 Appendix A

Appendix A presents the full Game Performance Index (GPI) formulas and supporting positional weighting tables referenced throughout the Results chapter. These materials are included to provide transparency regarding the calculation and application of the GPI framework while maintaining the readability of the main thesis. The appendix contains the position-specific formulas, variable weightings, and associated statistical tables used during the formula application process. These supplementary materials support the interpretation of the findings in section 4.7.

Table 1A. Experts' answers regarding the variables for the GPI Formula for a **Centre Back**.

<i>Likert Scale (1 to 5)</i>		1	2	3	4	5	%
Positive							
	<i>Aerial duel (won)</i>	0	0	0	0	7	100
	<i>Defensive duel (won)</i>	0	0	0	0	7	100
	<i>Dribble (successful)</i>	0	3	3	0	1	57.14
	<i>Interception (successful)</i>	0	0	0	1	6	100
	<i>Offensive duel (successful)</i>	0	3	2	1	1	57.14
	<i>Loose ball duel (successful)</i>	0	0	0	4	3	100
	<i>Chance created</i>	3	3	0	0	1	14.29
	<i>Pass to final third (successful)</i>	0	1	3	3	0	85.71
	<i>Pressing duel</i>	1	2	2	2	0	57.14
	<i>Shot (on target)</i>	3	3	1	0	0	14.29
	<i>Shot (goal)</i>	2	2	1	0	2	42.86
	<i>Progressive pass (successful)</i>	0	0	0	1	6	100
	<i>Lateral pass (successful)</i>	0	1	4	1	1	85.71
	<i>Forward pass (successful)</i>	0	0	1	1	5	100
Negative							
	<i>Aerial duel (Lost)</i>	0	0	0	0	7	100
	<i>Defensive duel (Lost)</i>	0	0	0	1	6	100
	<i>Dribble (unsuccessful)</i>	0	1	2	3	1	85.71
	<i>Fouls performed that originated dangerous situations</i>	0	0	0	0	7	100
	<i>Interception (unsuccessful)</i>	0	0	0	2	5	100
	<i>Offensive duel (unsuccessful)</i>	1	3	1	1	1	42.86
	<i>Loose ball duel (unsuccessful)</i>	0	0	1	4	2	100
	<i>Pass to final third (unsuccessful)</i>	1	0	3	3	0	85.71
	<i>Shot (off target)</i>	4	3	0	0	0	0
	<i>Shot (blocked)</i>	4	3	0	0	0	0
	<i>Progressive pass (unsuccessful)</i>	0	0	0	2	5	100
	<i>Lateral pass (unsuccessful)</i>	0	0	4	1	2	100
	<i>Forward pass (unsuccessful)</i>	0	0	1	2	4	100
	<i>Error leading to opposition chance (ELOC)</i>	0	0	0	0	7	100

%; percentage of number of the 7 participants that grade the variable a 3 or higher

Table 2A. Experts' answers regarding the variables for the GPI Formula for a **Full Back**.

		<i>Likert Scale (1 to 5)</i>					
	<i>Variable</i>	1	2	3	4	5	%
<i>Positive</i>							
	<i>Aerial duel (won)</i>	0	0	1	4	2	100
	<i>Defensive duel (won)</i>	0	0	0	0	7	100
	<i>Dribble (successful)</i>	0	0	2	3	2	100
	<i>Interception (successful)</i>	0	0	0	3	4	100
	<i>Offensive duel (successful)</i>	0	0	4	1	2	100
	<i>Loose ball duel (successful)</i>	0	0	2	3	2	100
	<i>Chance Created</i>	0	0	1	4	2	100
	<i>Pass to final third (successful)</i>	0	0	1	3	3	100
	<i>Pressing duel</i>	0	3	0	4	0	57.14
	<i>Shot (on target)</i>	1	2	4	0	0	57.14
	<i>Shot (goal)</i>	1	3	1	0	2	42.85
	<i>Progressive pass (successful)</i>	0	0	0	3	4	100
	<i>Lateral pass (successful)</i>	0	1	2	4	0	85.71
	<i>Forward pass (successful)</i>	0	0	0	2	5	100
<i>Negative</i>							
	<i>Aerial duel (Lost)</i>	0	0	1	4	2	100
	<i>Defensive duel (Lost)</i>	0	0	0	1	6	100
	<i>Dribble (unsuccessful)</i>	0	0	4	3	0	100
	<i>Fouls performed that originated dangerous situations</i>	0	0	0	2	5	100
	<i>Interception (unsuccessful)</i>	0	0	0	2	5	100
	<i>Offensive duel (unsuccessful)</i>	0	1	4	1	1	85.71
	<i>Loose ball duel (unsuccessful)</i>	0	0	3	2	2	100
	<i>Pass to final third (unsuccessful)</i>	1	0	2	3	1	85.71
	<i>Shot (off target)</i>	2	2	3	0	0	42.85
	<i>Shot (blocked)</i>	2	2	3	0	0	42.85
	<i>Progressive pass (unsuccessful)</i>	0	0	1	3	3	100
	<i>Lateral pass (unsuccessful)</i>	0	1	3	2	1	85.71
	<i>Forward pass (unsuccessful)</i>	0	1	0	3	3	85.71
	<i>Error leading to opposition chance (ELOC)</i>	0	0	0	0	7	100

%: percentage of number of the 7 participants that grade the variable a 3 or higher

Table 3A. Experts answer regarding the variables for the GPI Formula for a **Defensive Midfielder**

Likert Scale (1 to 5)							
	Variable	1	2	3	4	5	%
Positive	Aerial duel (won)	0	0	2	4	1	100
	Defensive duel (won)	0	0	0	2	5	100
	Dribble (successful)	0	1	4	1	1	85.71
	Interception (successful)	0	0	0	2	5	100
	Offensive duel (successful)	0	0	3	3	1	100
	Loose ball duel (successful)	0	0	0	4	3	100
	Chance Created	0	0	4	2	1	100
	Pass to final third (successful)	0	0	0	1	6	100
	Pressing duel	0	1	4	0	2	85.71
	Shot (on target)	0	0	5	2	0	100
	Shot (goal)	0	0	5	0	2	100
	Progressive pass (successful)	0	0	0	1	6	100
	Lateral pass (successful)	0	0	2	3	2	100
Forward pass (successful)	0	0	0	1	6	100	
Negative	Aerial duel (Lost)	0	0	2	4	1	100
	Defensive duel (Lost)	0	0	0	4	3	100
	Dribble (unsuccessful)	0	1	3	2	1	85.71
	Fouls performed that originated dangerous situations	0	0	0	2	5	100
	Interception (unsuccessful)	0	0	1	2	4	100
	Offensive duel (unsuccessful)	0	2	1	2	2	71.42
	Loose ball duel (unsuccessful)	0	1	0	2	4	85.71
	Pass to final third (unsuccessful)	0	0	1	1	5	100
	Shot (off target)	0	2	4	1	0	71.42
	Shot (blocked)	0	2	4	1	0	71.42
	Progressive pass (unsuccessful)	0	0	0	1	6	100
	Lateral pass (unsuccessful)	0	0	3	1	3	100
	Forward pass (unsuccessful)	0	0	0	1	6	100
Error leading to opposition chance (ELOC)	0	1	0	1	5	85.71	

%: percentage of number of the 7 participants that grade the variable a 3 or higher

Table 4A. Experts' answers regarding the variables for the GPI Formula for an **Attacking Midfielder**.

<i>Likert Scale (1 to 5)</i>						
	<i>Variable</i>	1	2	3	4	5 %
Positive	<i>Aerial duel (won)</i>	0	3	4	0	0 57.14
	<i>Defensive duel (won)</i>	0	1	4	0	2 85.71
	<i>Dribble (successful)</i>	0	0	1	4	2 100
	<i>Interception (successful)</i>	0	0	4	2	1 100
	<i>Offensive duel (successful)</i>	0	0	0	5	2 100
	<i>Loose ball duel (successful)</i>	0	1	3	1	2 85.71
	<i>Chance Created</i>	0	0	0	2	5 100
	<i>Pass to final third (successful)</i>	0	0	2	0	5 100
	<i>Pressing duel</i>	0	1	2	3	1 85.71
	<i>Shot (on target)</i>	0	0	0	5	2 100
	<i>Shot (goal)</i>	0	0	0	3	4 100
	<i>Progressive pass (successful)</i>	0	0	1	0	6 100
	<i>Lateral pass (successful)</i>	1	1	1	2	2 71.42
	<i>Forward pass (successful)</i>	0	0	0	1	6 100
Negative	<i>Aerial duel (Lost)</i>	0	3	4	0	0 57.14
	<i>Defensive duel (Lost)</i>	1	1	3	1	1 71.42
	<i>Dribble (unsuccessful)</i>	0	0	3	2	2 100
	<i>Fouls performed that originated dangerous situations</i>	0	1	5	0	1 85.71
	<i>Interception (unsuccessful)</i>	0	1	2	3	1 85.71
	<i>Offensive duel (unsuccessful)</i>	0	0	1	3	3 100
	<i>Loose ball duel (unsuccessful)</i>	0	2	1	1	3 71.42
	<i>Pass to final third (unsuccessful)</i>	0	0	2	1	4 100
	<i>Shot (off target)</i>	0	0	2	3	2 100
	<i>Shot (blocked)</i>	0	0	2	4	1 100
	<i>Progressive pass (unsuccessful)</i>	0	0	0	2	5 100
	<i>Lateral pass (unsuccessful)</i>	1	0	3	1	2 85.71
	<i>Forward pass (unsuccessful)</i>	0	0	1	1	5 100
	<i>Error leading to opposition chance (ELOC)</i>	0	2	1	1	3 71.42

%; percentage of number of the 7 participants that grade the variable a 3 or higher

Table 5A. Experts' answers regarding the variables for the GPI Formula for a **Winger**.

<i>Likert Scale (1 to 5)</i>		1	2	3	4	5	%
Positive							
	<i>Aerial duel (won)</i>	2	2	3	0	0	42.86
	<i>Defensive duel (won)</i>	1	2	3	0	1	57.14
	<i>Dribble (successful)</i>	0	0	0	0	7	100
	<i>Interception (successful)</i>	1	2	2	2	0	57.14
	<i>Offensive duel (successful)</i>	0	0	0	2	5	100
	<i>Loose ball duel (successful)</i>	1	2	2	2	0	57.14
	<i>Chance Created</i>	0	0	0	1	6	100
	<i>Pass to final third (successful)</i>	0	2	1	1	3	71.43
	<i>Pressing duel</i>	0	1	1	0	5	85.71
	<i>Shot (on target)</i>	0	0	0	4	3	100
	<i>Shot (goal)</i>	0	0	0	2	5	100
	<i>Progressive pass (successful)</i>	0	1	3	2	1	85.71
	<i>Lateral pass (successful)</i>	1	1	4	1	0	71.43
	<i>Forward pass (successful)</i>	0	0	4	0	3	100
Negative							
	<i>Aerial duel (Lost)</i>	2	2	3	0	0	42.86
	<i>Defensive duel (Lost)</i>	1	2	3	0	1	57.14
	<i>Dribble (unsuccessful)</i>	0	0	1	1	5	100
	<i>Fouls performed that originated dangerous situations</i>	1	2	3	0	1	57.14
	<i>Interception (unsuccessful)</i>	2	2	2	1	0	42.86
	<i>Offensive duel (unsuccessful)</i>	0	0	1	2	4	100
	<i>Loose ball duel (unsuccessful)</i>	0	4	1	1	1	42.86
	<i>Pass to final third (unsuccessful)</i>	0	0	3	1	3	100
	<i>Shot (off target)</i>	0	0	2	2	3	100
	<i>Shot (blocked)</i>	0	0	1	4	2	100
	<i>Progressive pass (unsuccessful)</i>	0	0	4	1	2	100
	<i>Lateral pass (unsuccessful)</i>	1	0	5	1	0	85.71
	<i>Forward pass (unsuccessful)</i>	0	0	4	1	2	100
	<i>Error leading to opposition chance (ELOC)</i>	0	2	3	0	2	71.43

%; percentage of number of the 7 participants that grade the variable a 3 or higher

Table 6A. Experts' answers regarding the variables for the GPI Formula for a **Centre Forward**

Likert Scale (1 to 5)							
	Variable	1	2	3	4	5	%
Positive	Aerial duel (won)	0	0	3	2	2	100
	Defensive duel (won)	0	3	3	0	1	57.14
	Dribble (successful)	0	1	1	4	1	85.71
	Interception (successful)	1	2	2	1	1	57.14
	Offensive duel (successful)	0	0	2	3	2	100
	Loose ball duel (successful)	1	3	0	2	0	33.33
	Chance Created	0	0	2	3	2	100
	Pass to final third (successful)	1	2	3	1	0	57.14
	Pressing duel	0	1	0	2	4	85.71
	Shot (on target)	0	0	0	0	7	100
	Shot (goal)	0	0	0	0	7	100
	Progressive pass (successful)	0	2	4	0	1	71.42
	Lateral pass (successful)	1	1	4	1	0	71.42
Forward pass (successful)	0	2	3	1	1	71.42	
Negative	Aerial duel (Lost)	0	0	1	5	1	100
	Defensive duel (Lost)	1	2	3	1	0	57.14
	Dribble (unsuccessful)	0	0	2	4	1	100
	Fouls performed that originated dangerous situations	2	2	2	0	1	42.85
	Interception (unsuccessful)	2	2	3	0	0	42.85
	Offensive duel (unsuccessful)	0	0	3	1	3	100
	Loose ball duel (unsuccessful)	0	4	1	1	1	42.85
	Pass to final third (unsuccessful)	2	2	2	0	1	42.85
	Shot (off target)	0	0	0	1	6	100
	Shot (blocked)	0	0	0	1	6	100
	Progressive pass (unsuccessful)	0	3	1	1	2	57.14
	Lateral pass (unsuccessful)	1	2	3	1	0	57.14
	Forward pass (unsuccessful)	0	2	2	2	1	71.42
Error leading to opposition chance (ELOC)	0	2	3	0	2	71.42	

%: percentage of number of the 7 participants that grade the variable a 3 or higher

10. Appendix B

Appendix B presents the full position-specific Game Performance Index (GPI) formulas developed from the coach-rated importance scores collected during the expertise evaluation stage. These formulas were generated using the standardised variable weightings assigned to each technical action for the six positional groups examined within the study. The appendix is included to provide transparency regarding the structure and calculation of the GPI framework while avoiding excessive technical detail within the main body of the thesis. The formulas presented support the interpretation of the findings discussed in Section 4.7 and demonstrate how coach perceptions were operationalised into a position-specific evaluative model.

Centre Back

$$\begin{aligned} &= 5.00 \times \left(\frac{\text{Aerial duel (won)}}{\text{Time Played}} \right) + 5.00 \times \left(\frac{\text{Defensive duel (won)}}{\text{Time Played}} \right) + 4.86 \times \left(\frac{\text{Interception (Successful)}}{\text{Time Played}} \right) + \\ &4.43 \times \left(\frac{\text{Loose Ball duel (Successful)}}{\text{Time Played}} \right) + 3.29 \times \left(\frac{\text{Pass to Final Third (Successful)}}{\text{Time Played}} \right) + 4.86 \times \\ &\left(\frac{\text{Progressive Pass (Successful)}}{\text{Time Played}} \right) + 3.29 \times \left(\frac{\text{Lateral Pass (Successful)}}{\text{Time Played}} \right) + 4.57 \times \left(\frac{\text{Forward Pass (Successful)}}{\text{Time Played}} \right) \\ &- 5.00 \times \left(\frac{\text{Aerial duel (Lost)}}{\text{Time Played}} \right) - 4.86 \times \left(\frac{\text{Defensive duel (Lost)}}{\text{Time Played}} \right) - 3.57 \times \left(\frac{\text{Dribble (Unsuccessful)}}{\text{Time Played}} \right) \\ &- 5.00 \times \left(\frac{\text{FPODS}}{\text{Time Played}} \right) - 4.71 \times \left(\frac{\text{Interception (Unsuccessful)}}{\text{Time Played}} \right) - 4.14 \times \left(\frac{\text{Loose Ball duel (Unsuccessful)}}{\text{Time Played}} \right) \\ &- 3.14 \times \left(\frac{\text{Pass to Final Third (Unsuccessful)}}{\text{Time Played}} \right) - 4.71 \times \left(\frac{\text{Progressive Pass (Unsuccessful)}}{\text{Time Played}} \right) - 3.71 \times \\ &\left(\frac{\text{Lateral Pass (Unsuccessful)}}{\text{Time Played}} \right) - 4.43 \times \left(\frac{\text{Forward Pass (Unsuccessful)}}{\text{Time Played}} \right) - 5.00 \times \left(\frac{\text{ELOC}}{\text{Time Played}} \right) \end{aligned}$$

Full Back

$$\begin{aligned}
&= 4.14 \times \left(\frac{\text{Aerial duel (won)}}{\text{Time Played}} \right) + 5.00 \times \left(\frac{\text{Defensive duel (won)}}{\text{Time Played}} \right) + 4.00 \times \left(\frac{\text{Dribble (Successful)}}{\text{Time Played}} \right) + \\
&4.57 \times \left(\frac{\text{Interception (Successful)}}{\text{Time Played}} \right) + 3.71 \times \left(\frac{\text{Offensive duel (Successful)}}{\text{Time Played}} \right) + 4.00 \times \left(\frac{\text{Loose Ball duel (Successful)}}{\text{Time Played}} \right) + \\
&4.14 \times \left(\frac{\text{Chance Created}}{\text{Time Played}} \right) + 4.29 \times \left(\frac{\text{Pass to Final Third (Successful)}}{\text{Time Played}} \right) + 4.57 \times \left(\frac{\text{Progressive Pass (Successful)}}{\text{Time Played}} \right) \\
&+ 3.43 \times \left(\frac{\text{Lateral Pass (Successful)}}{\text{Time Played}} \right) + 4.71 \times \left(\frac{\text{Forward Pass (Successful)}}{\text{Time Played}} \right) - 4.14 \times \left(\frac{\text{Aerial duel (Lost)}}{\text{Time Played}} \right) \\
&- 4.86 \times \left(\frac{\text{Defensive duel (Lost)}}{\text{Time Played}} \right) - 3.43 \times \left(\frac{\text{Dribble (Unsuccessful)}}{\text{Time Played}} \right) - 4.71 \times \left(\frac{\text{FPODS}}{\text{Time Played}} \right) \\
&- 4.71 \times \left(\frac{\text{Interception (Unsuccessful)}}{\text{Time Played}} \right) - 3.29 \times \left(\frac{\text{Offensive duel (Unsuccessful)}}{\text{Time Played}} \right) - 3.86 \times \\
&\left(\frac{\text{Loose Ball duel (Unsuccessful)}}{\text{Time Played}} \right) - 3.43 \times \left(\frac{\text{Pass to Final Third (Unsuccessful)}}{\text{Time Played}} \right) - 4.29 \times \\
&\left(\frac{\text{Progressive Pass (Unsuccessful)}}{\text{Time Played}} \right) - 3.43 \times \left(\frac{\text{Lateral Pass (Unsuccessful)}}{\text{Time Played}} \right) - 4.14 \times \left(\frac{\text{Forward Pass (Unsuccessful)}}{\text{Time Played}} \right) \\
&- 5.00 \times \left(\frac{\text{ELOC}}{\text{Time Played}} \right)
\end{aligned}$$

Defensive Midfielder

$$\begin{aligned}
&= 3.86 \times \left(\frac{\text{Aerial duel (won)}}{\text{Time Played}} \right) + 4.71 \times \left(\frac{\text{Defensive duel (won)}}{\text{Time Played}} \right) + 3.29 \times \left(\frac{\text{Dribble (Successful)}}{\text{Time Played}} \right) + \\
&4.71 \times \left(\frac{\text{Interception (Successful)}}{\text{Time Played}} \right) + 4.43 \times \left(\frac{\text{Loose Ball duel (Successful)}}{\text{Time Played}} \right) + 3.57 \times \left(\frac{\text{Chance Created}}{\text{Time Played}} \right) \\
&+ 4.86 \times \left(\frac{\text{Pass to Final Third (Successful)}}{\text{Time Played}} \right) + 3.43 \times \left(\frac{\text{Pressing duel}}{\text{Time Played}} \right) + 3.43 \times \left(\frac{\text{Shot (on target)}}{\text{Time Played}} \right) + \\
&3.57 \times \left(\frac{\text{Shot (goal)}}{\text{Time Played}} \right) + 4.86 \times \left(\frac{\text{Progressive Pass (Successful)}}{\text{Time Played}} \right) + 4.00 \times \left(\frac{\text{Lateral Pass (Successful)}}{\text{Time Played}} \right) \\
&+ 4.86 \times \left(\frac{\text{Forward Pass (Successful)}}{\text{Time Played}} \right) - 3.86 \times \left(\frac{\text{Aerial duel (Lost)}}{\text{Time Played}} \right) - 4.43 \times \left(\frac{\text{Defensive duel (Lost)}}{\text{Time Played}} \right) \\
&- 3.43 \times \left(\frac{\text{Dribble (Unsuccessful)}}{\text{Time Played}} \right) - 4.71 \times \left(\frac{\text{FPODS}}{\text{Time Played}} \right) - 4.43 \times \left(\frac{\text{Interception (Unsuccessful)}}{\text{Time Played}} \right) \\
&- 3.57 \times \left(\frac{\text{Offensive duel (Unsuccessful)}}{\text{Time Played}} \right) - 4.29 \times \left(\frac{\text{Loose Ball duel (Unsuccessful)}}{\text{Time Played}} \right) - 4.57 \times \\
&\left(\frac{\text{Pass to Final Third (Unsuccessful)}}{\text{Time Played}} \right) - 4.86 \times \left(\frac{\text{Progressive Pass (Unsuccessful)}}{\text{Time Played}} \right) - 4.00 \times \\
&\left(\frac{\text{Lateral Pass (Unsuccessful)}}{\text{Time Played}} \right) - 4.86 \times \left(\frac{\text{Forward Pass (Unsuccessful)}}{\text{Time Played}} \right) - 4.43 \times \left(\frac{\text{ELOC}}{\text{Time Played}} \right)
\end{aligned}$$

Attacking Midfielder

$$\begin{aligned}
&= 3.43 \times \left(\frac{\text{Defensive duel (won)}}{\text{Time Played}} \right) + 4.14 \times \left(\frac{\text{Dribble (Successful)}}{\text{Time Played}} \right) + 3.57 \times \left(\frac{\text{Interception (Successful)}}{\text{Time Played}} \right) + \\
&4.29 \times \left(\frac{\text{Offensive duel (Successful)}}{\text{Time Played}} \right) + 3.57 \times \left(\frac{\text{Loose Ball duel (Successful)}}{\text{Time Played}} \right) + 4.71 \times \left(\frac{\text{Chance Created}}{\text{Time Played}} \right) \\
&+ 4.43 \times \left(\frac{\text{Pass to Final Third (Successful)}}{\text{Time Played}} \right) + 3.57 \times \left(\frac{\text{Pressing duel}}{\text{Time Played}} \right) + 4.29 \times \left(\frac{\text{Shot (on target)}}{\text{Time Played}} \right) + \\
&4.57 \times \left(\frac{\text{Shot (goal)}}{\text{Time Played}} \right) + 4.71 \times \left(\frac{\text{Progressive Pass (Successful)}}{\text{Time Played}} \right) + 4.86 \times \left(\frac{\text{Forward Pass (Successful)}}{\text{Time Played}} \right) \\
&- 3.86 \times \left(\frac{\text{Dribble (Unsuccessful)}}{\text{Time Played}} \right) - 3.14 \times \left(\frac{\text{FPODS}}{\text{Time Played}} \right) - 3.57 \times \left(\frac{\text{Interception (Unsuccessful)}}{\text{Time Played}} \right) \\
&- 4.29 \times \left(\frac{\text{Offensive duel (Unsuccessful)}}{\text{Time Played}} \right) - 4.29 \times \left(\frac{\text{Pass to Final Third (Unsuccessful)}}{\text{Time Played}} \right) - 4.00 \times \\
&\left(\frac{\text{Shot (off target)}}{\text{Time Played}} \right) - 3.86 \times \left(\frac{\text{Shot (blocked)}}{\text{Time Played}} \right) - 4.71 \times \left(\frac{\text{Progressive Pass (Unsuccessful)}}{\text{Time Played}} \right) - 3.43 \times \\
&\left(\frac{\text{Lateral Pass (Unsuccessful)}}{\text{Time Played}} \right) - 4.57 \times \left(\frac{\text{Forward Pass (Unsuccessful)}}{\text{Time Played}} \right)
\end{aligned}$$

Winger

$$\begin{aligned}
&= 5.00 \times \left(\frac{\text{Dribble (Successful)}}{\text{Time Played}} \right) + 4.71 \times \left(\frac{\text{Offensive duel (Successful)}}{\text{Time Played}} \right) + 4.86 \times \left(\frac{\text{Chance Created}}{\text{Time Played}} \right) \\
&+ 4.29 \times \left(\frac{\text{Pressing duel}}{\text{Time Played}} \right) + 4.43 \times \left(\frac{\text{Shot (on target)}}{\text{Time Played}} \right) + 4.71 \times \left(\frac{\text{Shot (goal)}}{\text{Time Played}} \right) + 3.43 \times \\
&\left(\frac{\text{Progressive Pass (Successful)}}{\text{Time Played}} \right) + 3.86 \times \left(\frac{\text{Forward Pass (Successful)}}{\text{Time Played}} \right) - 4.57 \times \left(\frac{\text{Dribble (Unsuccessful)}}{\text{Time Played}} \right) \\
&- 4.43 \times \left(\frac{\text{Offensive duel (Unsuccessful)}}{\text{Time Played}} \right) - 4.00 \times \left(\frac{\text{Pass to Final Third (Unsuccessful)}}{\text{Time Played}} \right) - 4.14 \times \\
&\left(\frac{\text{Shot (off target)}}{\text{Time Played}} \right) - 4.14 \times \left(\frac{\text{Shot (blocked)}}{\text{Time Played}} \right) - 3.71 \times \left(\frac{\text{Progressive Pass (Unsuccessful)}}{\text{Time Played}} \right) - 3.71 \times \\
&\left(\frac{\text{Forward Pass (Unsuccessful)}}{\text{Time Played}} \right)
\end{aligned}$$

Centre Forward

$$\begin{aligned} &= 3.86 \times \left(\frac{\text{Aerial duel (won)}}{\text{Time Played}} \right) + 3.71 \times \left(\frac{\text{Dribble (Successful)}}{\text{Time Played}} \right) + 4.00 \times \left(\frac{\text{Offensive duel (Successful)}}{\text{Time Played}} \right) + \\ &4.00 \times \left(\frac{\text{Chance Created}}{\text{Time Played}} \right) + 4.29 \times \left(\frac{\text{Pressing duel}}{\text{Time Played}} \right) + 5.00 \times \left(\frac{\text{Shot (on target)}}{\text{Time Played}} \right) + 5.00 \times \left(\frac{\text{Shot (goal)}}{\text{Time Played}} \right) \\ &- 4.00 \times \left(\frac{\text{Aerial duel (Lost)}}{\text{Time Played}} \right) - 3.86 \times \left(\frac{\text{Dribble (Unsuccessful)}}{\text{Time Played}} \right) - 4.00 \times \left(\frac{\text{Offensive duel (Unsuccessful)}}{\text{Time Played}} \right) \\ &- 4.86 \times \left(\frac{\text{Shot (off target)}}{\text{Time Played}} \right) - 4.86 \times \left(\frac{\text{Shot (blocked)}}{\text{Time Played}} \right) \end{aligned}$$