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Predictive analysis of starting status in women's basketball: playing position and key performance indicators

Análisis Predictivo de la Titularidad en Baloncesto Femenino: Posición de Juego e Indicadores Clave de Rendimiento

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Abstract

This study analyses the factors influencing starting status in women's basketball, considering specific positions and individual performance indicators. Data from a full season of the Liga Endesa were used to conduct descriptive analysis, a chi-squared test of independence, and logistic regression models. The results show that point guards and power forwards have the highest proportions of starting status (57.1% and 66.4%, respectively), while shooting guards have the lowest (46.2%). The chi-squared test confirmed a significant relationship between position and starting status. In the predictive model, assists, successful field goals, and fouls received significantly increased the probability of starting status, while fouls committed reduced it. These findings highlight the importance of strategic positions and individual performance in the selection of starting players, providing valuable insights to optimize strategies in women's basketball. Point guards and power forwards emerge as key positions, while offensive performance and active participation in the game are critical determinants of starting status.

Keywords: women´s performance; predictive model; performance indicators; specific positions.

Resumen

Este estudio analiza los factores que influyen en la titularidad en el baloncesto femenino, considerando las posiciones específicas y los indicadores de rendimiento individual. Se utilizaron datos de una temporada completa de la Liga Endesa para realizar un análisis descriptivo, una prueba de independencia chi-cuadrado y modelos de regresión logística. Los resultados muestran que las bases y ala-pívots tienen las mayores proporciones de titularidad (57.1% y 66.4%, respectivamente), mientras que las escoltas presentan la menor (46.2%). La prueba chi-cuadrado confirmó una relación significativa entre posición y titularidad. En el modelo predictivo, las asistencias, tiros de campo logrados y faltas recibidas aumentaron significativamente la probabilidad de titularidad, mientras que las faltas cometidas la redujeron.
Estos hallazgos destacan la importancia de las posiciones estratégicas y el rendimiento individual en la elección de titularidad, proporcionando información valiosa para optimizar estrategias en el baloncesto femenino. Las bases y ala-pívots son posiciones clave, mientras que el rendimiento ofensivo y la participación activa en el juego son determinantes de titularidad.

Palabras clave: rendimiento femenino; modelo predictivo; indicadores de rendimiento; puestos específicos.

Introduction

In contemporary sports science, performance analysis has become increasingly crucial for teams and athletes pursuing competitive success (Lord et al., 2020). Within this context, basketball stands out as a sport where competition analysis and game statistics have been extensively utilized by both coaches and researchers to enhance team performance (García et al., 2014). Through systematic analysis, teams can identify and correct errors, understand opponent tendencies, and optimize training strategies to minimize in-game mistakes, ultimately increasing their chances of victory (Huyghe et al., 2021). As Mikes (1987) notably characterized it, basketball is fundamentally a science of percentages, where coaches harness data analysis with a singular objective: developing strategies to outscore their opponents. Advancing this conceptual understanding, more recent research emphasizes that performance analysis serves a dual purpose: first, to identify and develop team strengths through targeted training, and second, to address weaknesses before competition (Chen et al., 2025; Sarlis & Tjortjis, 2020). This analytical approach extends beyond self-assessment, providing valuable insights for developing strategic responses to opponents' capabilities and vulnerabilities.

The complexity of basketball as a multidimensional sport necessitates the analysis of numerous interconnected variables (Ibáñez et al., 2009; Canuto & de Almeida, 2022). Success in modern basketball increasingly depends on coaches' ability to understand and optimize these multiple performance factors. This perspective aligns with recent research highlighting how systematic recording and analysis of game indicators are fundamental for player development and tailored training programs (López-Sierra et al., 2024; Rogers et al., 2022; Rojas-Valverde et al., 2022). Within this analytical framework, starting lineup selection represents one of the most critical strategic decisions, directly influencing team performance and competitive outcomes through the establishment of tactical foundations, initial matchups, and game pace control (García et al., 2014; Zhou et al., 2024). The strategic deployment of specific player combinations in starting roles allows coaches to optimize team chemistry and exploit opponent weaknesses, making the understanding of position-specific performance indicators essential for effective lineup decisions (Ke et al., 2024).

Position-specific roles in basketball create distinct functional requirements and performance characteristics that significantly influence both individual and team dynamics (Ibáñez et al, 2024; Reina et al., 2020). Point guards serve as primary playmakers, orchestrating offensive strategies and modulating game pace through tactical decision-making. Shooting guards specialize in perimeter offense, executing spot-up shooting actions and off-ball tactical movements. Small forwards exhibit tactical versatility, implementing multi-level scoring strategies while providing defensive adaptability. Power forwards integrate interior presence with pick-and-pop efficiency, executing tactical actions from both low-post and high-post positions. Centers function as defensive anchors, optimizing spatial control through paint protection, defensive rebounding dominance, and establishing advantageous post positioning, thereby enhancing perimeter spacing dynamics (Anil-Duman et al., 2024). Although, this traditional classification has evolved due to the increasing number of versatile players in basketball competition (Rangel et al., 2019)

Performance indicators provide quantifiable metrics for evaluating game events' significance (Hughes & Frank, 2004). These indicators have demonstrated reliable correlations with game outcomes, making them valuable tools for performance assessment and prediction (García et al., 2013). Contemporary performance analysis must consider multiple contextual factors include player roles, competition phase (regular season versus playoffs), competition level (national, European, or international), game location (home or away), and match outcomes (Escudero-Tena et al., 2021; Fernández-Cortés et al., 2021; Plakias et al., 2024). Other studies relate these variables to physical demands to provide information for coaches and support staff for improvement of the athlete's performance (Calderani-Junior et al., 2020; Gómez-Carmona et al., 2019; Moreno-Ariza et al., 2023). This multifaceted approach provides a more comprehensive understanding of performance dynamics.

Given this theoretical framework, the present study aims to analyze the relationship between players' specific positions, game statistics, and starting lineup selection in women's professional basketball. Specifically, we examine key performance indicators (KPIs) influencing starter selection throughout a complete season of the Liga Endesa women's basketball league. We hypothesize that positionally-specific performance indicators will influence starter selection: guards through playmaking efficiency and shooting accuracy, forwards through defensive versatility and multi-positional scoring, and centers through interior dominance and rebounding effectiveness.

Materials and Methods

Design

According to the classification established by Montero and León (2007), this research constitutes a descriptive and analytical study employing naturalistic observation, wherein study factors are neither intervened with nor manipulated. Instead, these factors are observed under natural conditions in their real-world context.

Participants

The sample comprises 409 games from the Spanish Women's Basketball League "Liga Endesa" during the 2019/2020 and 2020/2021 seasons. In the first season, the league consisted of Spain's top 14 teams, while the latter season expanded to 16 teams due to the suspension of the 2019/2020 season caused by COVID-19. This suspension led to a decision to eliminate relegation while maintaining promotion, accounting for the additional two teams. The Liga Endesa structure consists of a regular phase with home and away matches between all teams, followed by a Play-Off phase involving the top 8 teams from the regular season. These Play-Offs comprise home and away quarter-finals and semi-finals, culminating in a best-of-three finals series.

The 409 sampled games encompass 22 matchdays from the 2019/2020 Regular Phase, and 30 matchdays from the Regular Season plus 7 Play-Off games from the 2020/2021 season. Statistics were collected for every player who participated for at least 1 second (7,777 players in total) across these matches for subsequent analysis.

Instruments

Data collection was conducted using a spreadsheet in *Microsoft Office Excel 365* software. Following data compilation, statistical analysis was performed using *R 4.3.2* data analysis software.

Procedures

Initially, to commence the recording of game indicators, an Excel spreadsheet was developed incorporating all variables intended for study. Each variable was assigned a numerical code, with additional columns for player names and team affiliations to facilitate efficient and systematic data recording.

Subsequently, statistical data corresponding to the 2019/2020 and 2020/2021 seasons were collected from the official Liga Femenina Endesa website and the Spanish Basketball Federation official website for subsequent analysis. Following data collection, the dataset was transferred to *R 4.3.2* software for conducting the necessary statistical analyses to address the study's objectives.

The independent variables comprised: (a) players' starting status (starter [S], non-starter [NS]), and (b) specific playing position (point guard [PG], shooting guard [SG], small forward [SF], power forward [PF], and center [C]). The dependent variables consisted of 20 game indicators (GI) grouped by statistical nature: *Temporal variables*: (1) minutes played (MIN); *Scoring variables*: (2) points scored (PTS), (3) two-point field goals attempted (2PA), (4) three-point field goals attempted (3PA), (5) two-point field goals made (2PM), (6) three-point field goals made (3PM), (7) total field goals attempted (FGA), (8) free throws attempted (FTA), (9) total field goals made (FGM), and (10) free throws made (FTM); *Rebounding variables*: (11) offensive rebounds (OREB), (12) defensive rebounds (DREB), and (13) total rebounds (REB); *Playmaking and ball-*

handling variables: (14) assists (AST), (15) steals (STL), and (16) turnovers (TOV); *Defensive variables*: (17) blocks made (BLK) and (18) blocks received (BLKR); *Foul-related variables*: (19) fouls committed (FC) and (20) fouls received (FR).

Statistical analysis

Data preprocessing required the conversion of categorical independent variables into factor levels for appropriate parametric analysis, while dependent variables underwent screening for missing values with mean imputation applied where necessary. A comprehensive descriptive statistical analysis was conducted, computing measures of central tendency and dispersion for all variables under investigation.

To examine the association between players' positional roles and starting status, a Pearson's chi-square test of independence was implemented (Thomas et al., 2022). Post-hoc analysis of standardized residuals was conducted to identify significant position-starter status combinations that contributed to the overall association pattern. The magnitude of these associations was evaluated through standardized residual analysis.

Binary logistic regression modeling was employed through a hierarchical approach (Hoffmann, 2021). The baseline model incorporated only positional predictors, while the expanded model integrated both positional and performance-based predictor variables. Model comparison and selection procedures utilized Akaike Information Criterion (*AIC*) and likelihood ratio tests through deviance analysis. The expanded model demonstrated superior fit indices ($p<.05$), supporting the inclusion of performance metrics in predicting starter status.

Model optimization was achieved through backward elimination of non-significant predictors ($p>.05$), resulting in a parsimonious final model. The retained significant predictors included assists per minute, fouls received, and field goal conversion rate. All statistical analyses were executed using *R* statistical software (R Core Team, 2020), with statistical significance established at $p<.05$.

Results

Figure 1 describes the study's dependent variables according to their mean and standard deviation. Variables with high means and variability, such as points per minute (PTmin) and field goal attempts per minute (FGAmin), could serve as robust indicators of individual performance and their impact on the probability of being selected as a starter.

A cross-tabulation frequency analysis was conducted to examine the distribution of starters and non-starters across specific playing positions. This analysis identified key patterns in the position-starter status relationship. For each position, the proportion of starters and non-starters was calculated, revealing differences in starting probability by position (Figure 2). Power forwards showed the highest proportion of starters (66.4%), followed by point guards (57.1%). Conversely, shooting guards demonstrated the lowest proportion of starters (46.2%).

The chi-square statistic was significant ($\chi^2_4 = 166.33$; $p < 2.2^{-16}$), indicating a statistically significant association between players' positions and their probability of being starters. Standardized residuals (Figure 3) identified that starting power forwards and non-starting shooting guards contributed notably to this relationship. This analysis confirms that specific positions significantly affect starting probability. Particularly, power forwards and point guards have higher representation as starters compared to shooting guards.

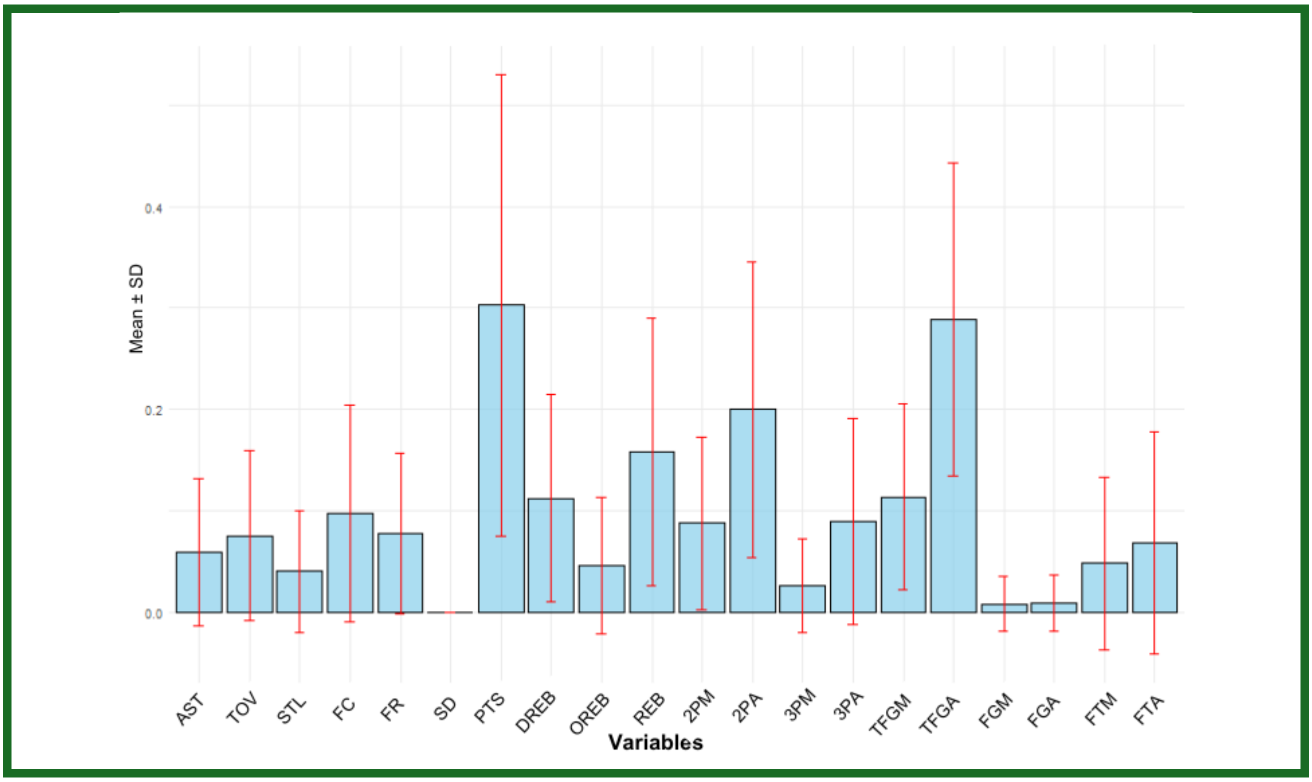

Figure 1. Representation of descriptive analysis values for the study's dependent variables (mean and standard deviation).

Figure 2. Proportion of starting and non-starting players in Liga Endesa by specific positions.

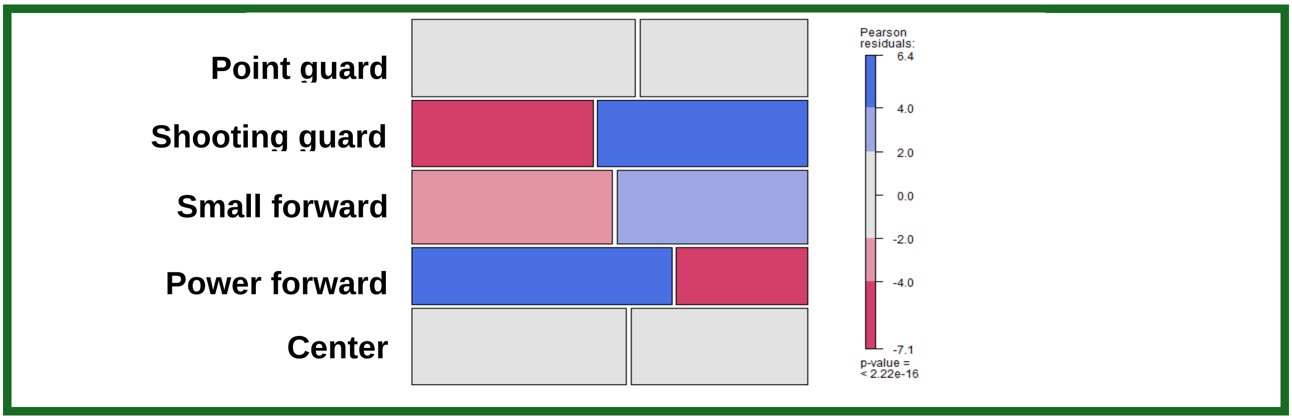

Figure 3. Relationship between starter status and specific position.

A binary logistic regression model was fitted to analyze how players' specific positions and game statistics influence the probability of being a starter. This model identified which factors significantly contribute to starter status and quantified their effect in terms of *odds* ratios. Initially, a model including only players' positions as predictors was fitted (Figure 4). Shooting guards (*OR*=0.66, *p*<0.05) and centers (*OR*=0.79, *p*<0.05) showed lower odds of being starters compared to point guards. Power forwards (*OR*=1.20, *p*<0.05) demonstrated significantly higher odds of starting compared to point guards.

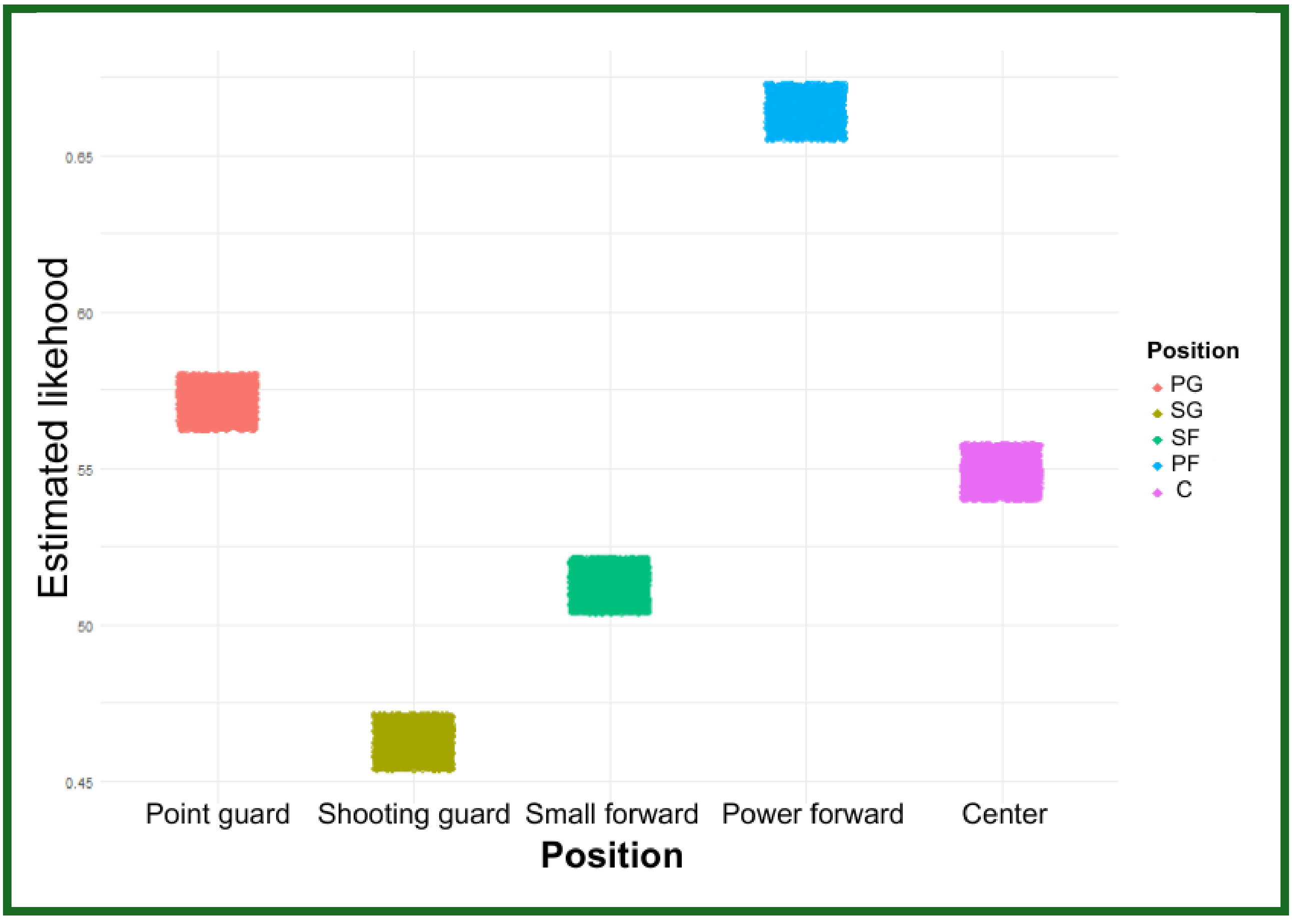

Figure 4. Probability of being a starter based on specific position according to the initial predictive model.

An extended model was also implemented to include the study's dependent variables, representing standard game indicators. This model identified significant variables related to starting probability. Variables such as assists (*ASmin*, *OR*=15.98, $p<0.05$), field goal attempts (*FGAmin*, *OR*=8.26, $p<0.05$), and fouls received (*FRmin*, *OR*=9.60, $p<0.05$) emerged as KPIs of starter status; while fouls commited (*FCmin*, *OR*=0.048, $p<0.05$) and free throws attempted (*FTAmin*, *OR*=0.126, $p<0.05$) acted as negative factors significantly reducing the odds of starting. The reduction in AIC (initial model=14308.98; extended model=13372.92) indicates that game indicators contribute relevant information to the model. Moreover, the significant reduction in deviance (ΔD=976.07, $p<2.2\times10^{-16}$) confirms that the extended model explains more variability in starter status than the initial model.

Figure 5a) illustrates the relationship between assists per minute (ASmin) and the predicted probability of starting status for each specific position. Individual observations are represented by points, and the fitted curves with confidence intervals reflect the probabilities predicted by the extended model. Across all positions, higher assists per minute are associated with a progressive increase in starting probability. The curve gradients indicate this effect is particularly pronounced in certain positions, such as point guards and power forwards. Point guards demonstrate the highest starting probability at any assist level, while shooting guards and centers show slightly lower starting probabilities compared to point guards, though still exhibiting an increase with higher assists. Power forwards show an effect similar to point guards, with elevated starting probabilities at intermediate and high assist levels. Small forwards display the lowest starting probability across ASmin values, reflecting a reduced impact of assists in this position. The shaded confidence interval around the curves widens at high assists per minute levels, indicating greater prediction uncertainty due to fewer players with extreme values.

Generally, the probability of starting status increases with higher field goal attempts per minute, particularly for low to intermediate FGAmin values (Figure 5b). However, for some positions, this relationship appears to stabilize or even decrease at high attempt levels. Point guards maintain consistently high starting probabilities across all FGAmin levels. Their probability increases rapidly at low attempt levels and stabilizes at higher levels. Conversely, shooting guards show an inverse behavior at high attempt levels, where starting probability decreases. This might reflect a negative impact of high shot volume in this position. Small forwards have generally lower probabilities, showing a slight tendency toward stabilization at intermediate attempt levels. Power forwards, similar to point guards, demonstrate a positive relationship between shot attempts and starting probability, with high values throughout the curve. Finally, centers show an initial probability increase with shot volume but tend to stabilize at higher levels. Confidence intervals widen at high FGAmin levels, indicating greater prediction uncertainty due to fewer observations at these extremes.

Regarding fouls received (FRmin; Figure 5c), starting probability increases progressively with this variable across all positions. Fouls received appear to be a positive indicator of starting status, highlighting the importance of players who draw physical contact due to their game influence. Point guards show a very pronounced relationship between fouls received and starting status, reaching probabilities near 100% at high FRmin levels. Shooting guards, however, demonstrate a more moderate increase in starting probability relative to fouls received, while maintaining a positive relationship. Small forwards show lower overall starting probability, though it also increases with higher FRmin levels. Power forwards have a starting probability that increases similarly to point guards, though slightly lower at high levels. Centers exhibit a moderate probability increase, with stabilization at high FRmin levels. Confidence intervals widen at high FRmin levels, indicating greater prediction uncertainty for players with extreme values.

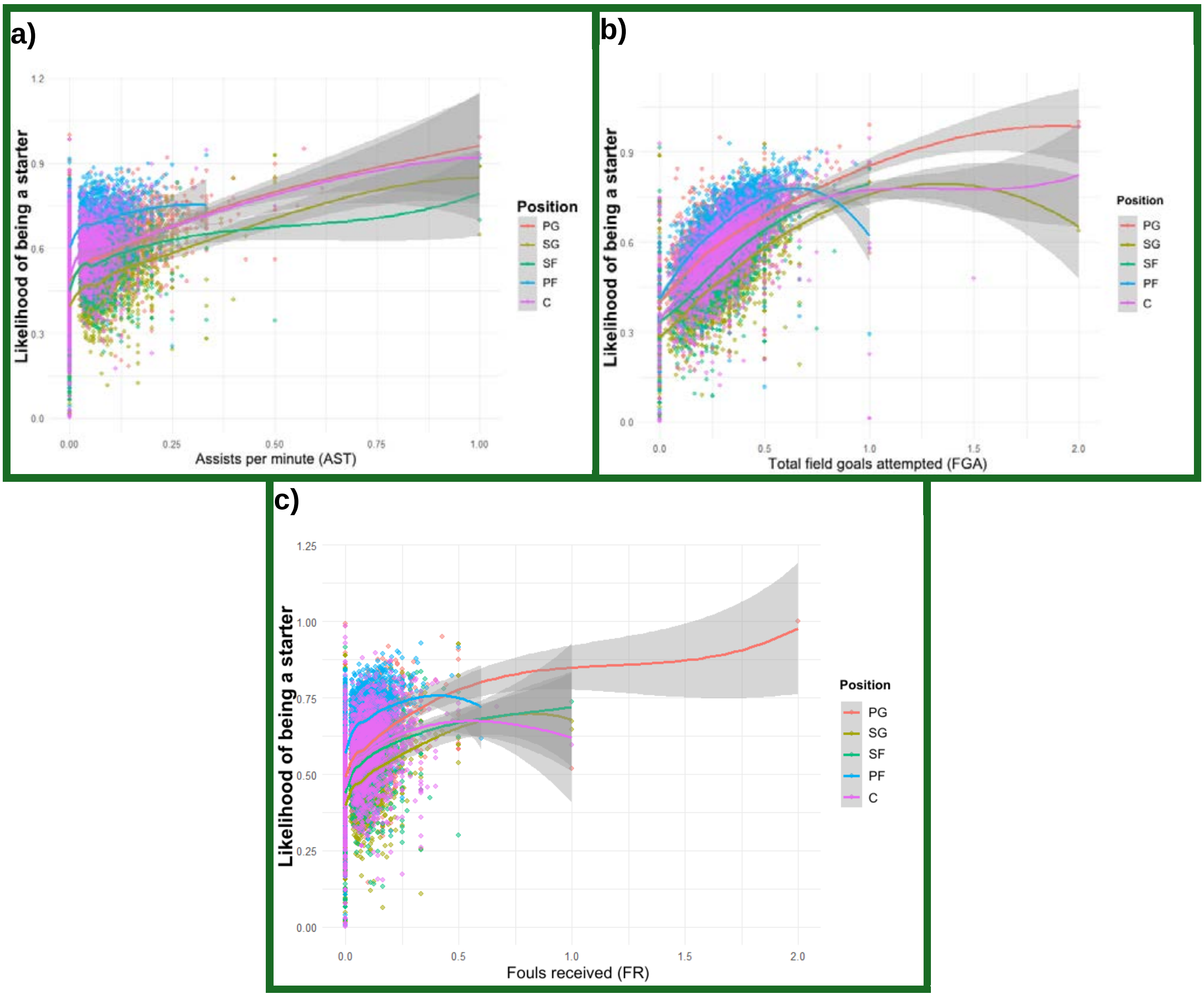

Figure 5. Probability of being a starter based on specific position and significant dependent variables from the extended predictive model: a) assists per minute (ASmin); b) field goal attempts per minute (FGAmin); c) fouls received per minute (FRmin).

Discussion

The present study examined the relationship between specific playing positions, game-related statistics, and starting status in women's professional basketball, addressing a significant gap in performance analysis literature. Through analysis of 409 games from the Liga Endesa, our research revealed that playing position significantly influences starting status, with power forwards (66.4%) and point guards (57.1%) showing the highest proportion of starters. These findings align with contemporary understanding of basketball as a multidimensional sport where position-specific roles create distinct functional requirements and performance characteristics that significantly influence both individual and team dynamics (Ibáñez et al., 2009; Reina et al., 2020).

The higher proportion of power forwards and point guards in starting lineups reflects the evolution of modern women's basketball tactical systems. Point guards' elevated starting status (57.1%) demonstrates their essential role in offensive direction, supporting findings by Zhai et al. (2021) who determined that guards and centers performance metrics were the strongest predictors of team success in women's basketball across all continents. This result also aligns with male players' patterns, where point guards demonstrated the highest influence on game pace and offensive efficiency during Olympic Games (Leicht et al., 2017). The dominance of power forwards in starting positions (66.4%) corroborates research by

Rangel et al. (2019), who identified the growing importance of versatile frontcourt players in the Brazilian National League, where small forwards and power forwards exhibited the most rapid growth in tactical versatility.

The significant positive relationship between assists per minute and starting probability across positions demonstrates the evolving nature of playmaking responsibilities in modern basketball. This finding was supported by Canuto & de Almeida (2018), whose systematic review and meta-analysis of basketball match outcome determinants classified assists and defensive rebounds as very good (Structural Coefficients, SC >0.56) and good (SC >0.46) discriminant factors of winning, respectively. The strong effect observed for power forwards aligns with Gasperi et al. (2020), who documented that high-ability forwards presented higher assist percentages, regardless of national or foreign player status in the Women's Basketball Euroleague.

Field goal attempts emerged as a significant positive predictor of starting status, though with interesting positional variations. The positive relationship for point guards and power forwards supports research by Leicht et al. (2017), who analyzed four Olympic tournaments of women's basketball and found that successful teams demonstrated higher field goal attempt rates as the primary factor in classification trees. However, the decreased probability for shooting guards at high attempt levels suggests tactical evolution in the contemporary game, aligning with Hatem et al. (2020) regarding shot selection patterns in women's basketball according to playing positions.

The positive impact of fouls received on starting probability, particularly strong for point guards and power forwards, supports research by Canuto & de Almeida (2021), who identified free throw generation as a KPI in successful women's teams. This relationship is further validated by Zhou et al. (2024), who found that elite women players' ability to draw fouls significantly influenced playing time and game outcomes. The negative relationship between fouls committed and starting status aligns with research by Piñar et al. (2022) and reflects the importance of defensive efficiency highlighted by García et al. (2014), who emphasized how competition analysis and game statistics are crucial for optimizing team performance.

The lower starting probabilities observed for shooting guards (46.2%) represents an evolution from traditional basketball theory but aligns with recent research by Fort-Vanmeerhaeghe et al. (2016), who documented evolving role definitions in women's basketball. This trend is further supported by Rangel et al. (2019), who noted increasing tactical flexibility across positions in modern basketball systems. These findings also correspond with research by Hatem et al. (2020), who observed that successful women's teams often featured less position-specific role distribution, reflecting the sport's contemporary tactical evolution.

The interaction between physical demands and position-specific performance metrics supports research by Ibáñez et al. (2023), who found that positional roles significantly influenced performance patterns in professional women's basketball players. This finding aligns with the broader understanding of basketball as a complex sport requiring analysis of multiple interconnected variables (Ibáñez et al., 2009) and the importance of systematic recording and analysis of game indicators for player development (Lord et al., 2020; Sarlis & Tjortjis, 2020).

Finally, although the present manuscript presents a first approach about the KPI that predict be a starter player in female basketball, several limitations should be considered when interpreting these results. First, the study's data spans only two seasons of the Liga Endesa, potentially limiting the generalizability of findings to other leagues or longer time periods. Additionally, the analysis doesn't account for team-specific tactical systems or coaching philosophies, which might influence starting lineup decisions independently of individual performance metrics. The impact of situational variables such as opponent strength, game location, and rest days between games was not considered in the current analysis.

To normalize the data, future research could consider projecting performance indicators to a 40-minute game duration. Furthermore, it is recommended that forthcoming studies differentiate between three playing positions — point guard, wing, and post — reflecting the evolving tactical roles within basketball. It is also advisable to exclude players who participate for less than one minute per game or who have played in fewer than 40% of the season’s fixtures. In addition, future research should examine these relationships across multiple professional leagues and longer time periods to validate these findings' generalizability. Investigation of how these relationships might vary between regular season and playoff games could provide additional insights into tactical adaptations in high-stakes situations. Furthermore, incorporating advanced metrics such as spacing data and defensive impact measures could enhance our understanding of position-specific contributions to team success.

Conclusions

The results of this study provide empirical evidence about the factors that influence starting status in professional women's basketball. There is a significant relationship between specific position and the probability of being a starter, with power forwards (66.4%) and point guards (57.1%) showing the highest proportions of starting status. In addition, the performance indicators that significantly increase the probability of being a starter are assists per minute, field goal attempts, and fouls received, while fouls committed, and free throws attempted reduce it. The effectiveness in offensive decision-making, reflected in assists and field goal attempts, emerges as a determining factor in the selection of starting players. The impact of these indicators varies according to specific position, being especially relevant for point guards and power forwards, which suggests the importance of considering positional role when evaluating individual performance. Finally, the predictive model developed demonstrates that the combination of specific position and performance indicators provides a more accurate tool for predicting starting status than considering playing position alone.

Practical applications

The findings from this study offer several valuable insights that coaches and practitioners can directly apply to enhance team performance and optimize player selection in women's basketball:

Prioritize development of power forwards and point guards (66.4% and 57.1% starting probability) through specific tactical systems and tailored training programs, as these positions show the highest impact on starting lineup selection.

Focus on assists per minute across all positions by implementing offensive systems promoting ball movement, developing playmaking abilities, and designing training drills focused on decision-making and passing skills.

Emphasize efficient field goal attempts, particularly for point guards and power forwards, through position-specific shooting drills, shot selection training, and offensive schemes that create optimal shooting opportunities.

Develop strategies to effectively received fouls while minimizing fouls committed through proper defensive positioning, strategic foul management, and training in techniques for receiving legitimate fouls.

Implement a comprehensive performance monitoring system focusing on KPIs: assists per minute, field goal attempt rates by position, and foul differential (drawn vs. committed).

Design specific player development programs focusing on: improving assist-to-minute ratios, developing efficient shot selection while maintaining high attempt rates, and balancing aggressive play with foul avoidance.

Create position-specific training protocols emphasizing playmaking for point guards, interior-exterior balance for power forwards, and minimizing unnecessary fouls across all positions.

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