DOI: 10.4025/jphyseduc.v36i1.3647

**Original Article**

# GAME-RELATED PERFORMANCE METRICS DIFFERENTIATING WINNING AND LOSING TEAMS IN THE BASKETBALL CHAMPIONS LEAGUE

## MÉTRICAS DE DESEMPENHO RELACIONADAS AO JOGO QUE DIFERENCIAM EQUIPES VENCEDORAS E PERDEDORAS NA LIGA DOS CAMPEÕES DE BASQUETE

**Panagiotis F. Foteinakis[1], Stefania P. Pavlidou[1]**

[1]Democritus University of Thrace, Komotini, Greece.

**RESUMO**
Este estudo teve como objetivo identificar variáveis de desempenho relacionadas ao jogo que diferenciam equipes vencedoras e perdedoras na Basketball Champions League e determinar os preditores mais significativos dos resultados dos jogos. Dados foram coletados de 175 jogos durante a temporada 2023-2024. O teste U de Mann-Whitney e a análise de regressão logística foram empregados para avaliar a influência do ataque e das métricas nos resultados dos jogos. Diferenças significativas foram encontradas em métricas-chave, como porcentagens de arremessos, pontos por jogo e rebotes defensivos, com as equipes vencedoras superando consistentemente as equipes perdedoras. A regressão logística identificou roubos de bola e rebotes defensivos como os preditores mais fortes de sucesso. Roubos de bola aumentaram as chances de vitória em 59,6% e rebotes defensivos em 48,8%, ressaltando o papel crítico das métricas defensivas. Por outro lado, tentativas de dois pontos previram negativamente as chances de vitória, com cada tentativa adicional reduzindo a probabilidade de vitória em 32,9%. As descobertas destacam a importância da eficiência na realização de arremessos, da defesa eficaz e da coordenação ofensiva no desempenho do basquete. Esses resultados fornecem insights valiosos para treinadores e analistas que buscam aprimorar o desempenho da equipe e desenvolver estratégias de jogo eficazes.
**Palavras-chave**: desempenho no basquete; eficiência ofensiva; métricas defensivas; análise de jogo; Liga dos Campeões de Basquete.

**ABSTRACT**
This study aimed to identify game-related performance variables that differentiate winning and losing teams in the Basketball Champions League and determine the most significant predictors of game outcomes. Data were collected from 175 games during the 2023-2024 season. The Mann-Whitney U test and logistic regression analysis were employed to evaluate the influence of offensive and defensive metrics on game outcomes. Significant differences were found in key metrics such as shooting percentages, points per game, and defensive rebounds, with winning teams consistently outperforming losing teams. Logistic regression identified steals and defensive rebounds as the strongest predictors of success. Steals increased the odds of victory by 59.6% and defensive rebounds by 48.8%, underscoring the critical role of defensive metrics. Conversely, two-point attempts negatively predicted winning odds, with each additional attempt reducing the likelihood of victory by 32.9%. The findings highlight the importance of efficient shot-making, effective defense, and offensive coordination in basketball performance. These results provide valuable insights for coaches and analysts seeking to enhance team performance and develop effective game strategies.
**Keywords**: basketball performance; offensive efficiency; defensive metrics; game analysis; Basketball Champions League.

## Introduction

The primary challenge for sports performance team members is to discover and analyze reliable indicators of team performance and identify game factors that can discriminate between successful and less successful teams. Basketball is a sport in which the distinction between winning and losing teams often comes down to the specific game-related performance variables that each team can leverage during the game. Identifying these game-related metrics can provide valuable insights for coaches and teams seeking to optimize their strategies and improve their chances of success.

Quantitative analysis of performance-related statistics has been widely used in basketball to evaluate team and player performance[1]. In basketball, performance cannot be fully understood without considering the interplay between offensive, defensive, and transition moments, as each reflects different strategic and tactical demands. Offensive phases focus on shot creation and efficiency, ball movement, and spacing, while defensive phases emphasize disrupting the offense, controlling rebounds, and generating turnovers. Transition moments occur between, connecting these phases, leveraging quick decision-making to create high-percentage scoring opportunities. By analyzing metrics within and across these game moments, such as points scored, rebounds, assists, turnovers, and shooting efficiency, coaches and analysts can gain valuable insights into the factors that contribute to the successful outcome of the game. These statistical measures provide an objective foundation that is a constructive basis for measuring relative performance[2]. Furthermore, quantitative analysis facilitates the identification of the game-related performance factors that differentiate successful teams, offering a basis for scouting, game preparation, and player development[3].

A substantial body of scientific research has uncovered game-related performance statistics that distinguish winning from losing teams at various competitive levels in national and collegiate championships[1,2,4-9] and predict final team rankings[10]. Defensive rebounds, assists, and shooting efficiency have appeared as recurring key indicators across multiple studies.

The majority of this research focuses on top-level professional leagues such as the NBA and the EuroLeague. Zhou et al.[11] revealed that game outcomes in the NBA were associated with two and three-point percentages, rebounds, assists, turnovers, steals, fouls, and game pace, while Cabarkapa et al.[9] identified the field goal percentage and defensive rebounds as the primary performance parameters that differentiate winners and losers over three NBA seasons. Mateus et al.[12] highlighted that in close NBA games, players tend to prioritize ball sharing and long-distance shooting. Similarly, Mikolajec, Maszczyk and Zajac[13] found offensive efficiency, fouls, and steals to be critical indicators of winning teams, whereas Melnick[14] emphasized the importance of teamwork and increased total assists for success.

At the EuroLeague level, Ektirici[15] suggested focusing on field goal shooting, defensive rebounding, and assists in improving team performance. Mikolajec et al.[16] revealed strong correlations between success and factors like assists, fouls, and made field goals. Çene[17], analyzing the 2016–2017 EuroLeague season, noted that shot quality was more important than quantity in close games, whereas the opposite was true for balanced and unbalanced games. Moreover, Özmen[18] demonstrated that superior turnovers, defensive rebounding, assists, and shooting accuracy characterized better performing teams. Similarly, Trninić, Dizdar and Luksić[19] identified defensive rebounds as the most critical factor, followed by field goal and free-throw shooting percentages.

In international competitions, Stavropoulos et al.[20] highlighted the significance of assists, free-throw attempts, and defensive rebounds in determining winning outcomes during the 2019 World Men's Basketball Championship. Leicht, Gómez and Woods[21], analyzing Men's Olympic basketball tournaments from 2004-2016, found that field-goal percentage and defensive rebounds were the strongest predictors of success, achieving a 93.2% probability of winning. Simonovic et al.[22] identified shooting effectiveness and defensive rebounding as key influences on final scores during the FIBA Asia Basketball Cup, while Csataljay et al.[23] examining the European Championship of 2007, found that three-point attempts, three-point and free-throw percentage, and defensive rebounds were critical in differentiating winning and losing teams. Comparing Asian and European contexts, Madarame[24] revealed that defensive rebounds and assists were decisive for winning in FIBA Asia games, while defensive rebounds alone played a similar role in European tournaments. Karipidis et al.,[2] analyzing games from major European, Olympic, and World Championships, indicated defensive rebounds, successful two and three-point shots, and missed three-point shots as top performance indicators, while Fotinakis et al.[25] added that field goals, turnovers, missed free throws, and both defensive and offensive rebounds significantly predicted team rankings during the European Championship in France.

The FIBA Basketball Champions League (BCL) represents a preeminent European competition. While the literature predominantly focuses on top-level leagues and international and collegiate tournaments, their findings are often league-specific, context-bound, or based on datasets collected under different tactical and temporal trends. To our knowledge, quantitative analysis of game-related statistics in BCL remains largely underexamined, as no studies have examined the contribution of game-related performance statistics to success in the BCL tournament. This study addresses this gap by integrating both traditional and advanced metrics across offensive, defensive, and transition moments. This approach not only allows for the identification of consistent predictors of success but also evaluates whether recent strategic evolutions, such as the growing reliance on three-point shooting and pace variation, have shifted the relative importance of these predictors compared to earlier studies. Thus, this study aimed to identify game-related performance variables that differentiate winning and losing teams in the BCL and determine the most significant predictors of game outcomes.

## Methods

*Sample and Data Collection*

Data was collected from the official box scores from all the games played in all phases of the BCL competition in the season 2023-2024, excluding only the Final Four due to its unique characteristics. This approach enables researchers to derive insights broadly applicable to typical game scenarios rather than specialized events. Publicly available BCL game-related statistics were obtained from the BCL official site (https://www.fiba.basketball/en/history/112-fiba-mens-european-club-competitions-tier-1/208737/games). The total number of games examined in the present study was 175, composed of 96 regular season games, 21 play-in games, 48 round of 16 games, and 10 quarter-finals games. Due to the public availability of the BCL game-related statistics, the Institutional Review Board’s approval for conducting this project was not needed[26].

*Variables and Procedure*

For the data analysis, the following game-related statistics were used: field goals made (FGM), field goals attempted (FGA), field goals percentage (FG%), 2-point shots made (2PM), 2-point shots attempted (2PA), 2-point percentage (2P%), 3-point shots made (3PM), 3-point shots attempted (3PA), 3-point percentage (3P%), free-throws made (FTM), free-throws attempted (FTA), free-throw percentage (FT%), offensive rebounds (OFFREB), defensive rebounds (DEFREB), assists (AST), personal fouls (PF), turnovers (TO), steals (ST) and points per game (PPG).

Moreover, the analysis included statistics derived from the box score and involved the following offensive efficiency metrics: effective field goal percentage (eFG%), true scoring percentage (TS%), and offensive rating (ORTG). eFG% provides a pace-independent measure of overall shooting efficiency by accounting for the added value of three-point field goals. The metric is calculated using the formula: eFG%=(FGM+0.5*3PM)/FGA[27], where FGM =field goals made, 3PM=3-point field goals made, and FGA=field goals attempted. This formula incorporates two and three-point field goals into a single measure, offering a comprehensive assessment of a team's shooting effectiveness[27].

TS% is a statistic that factors a team's performance at the free-throw line and considers the efficiency of all types of shots. It can be considered the clearest and easily measured metric that boils all three scoring methods into one number. The metric is calculated using the formula: TS%=Pts/(2 * (FGA + (0.44 * FTA))), where Pts=the total points scored, FGA= field goal attempted, FTA= free throws attempted[27].

Ball possessions (POSS) were calculated with the bellow formula: POSS =Field Goals attempted + (0.4 * Free Throws Attempted) + Turnovers – Offensive Rebounds[27]. A possession is every sequence of events a team creates until they score a basket (including free throws) or lose the ball. A powerful and widely used metric is the offensive rating (ORTG), which tries to capture the ability of a team to score each time they get the ball. The formula is: ORTG = PTS/POSS × 100[27].

*Statistical Analysis*

All variables were presented as mean ± standard deviation (M±SD). The data was initially explored for outliers, missing values, and extreme skewness. No missing values were observed, and the variables were retained without transformations. The Kolmogorov-Smirnov test assessed the normality assumption and revealed a non-normal data distribution. The Mann-Whitney U test was utilized to evaluate the differences in the examined variables between the winning and losing teams. Rank biserial correlation ($r$) was used to calculate the measure of effect size between game-related parameters and the game outcome ($r$<0.3=small effect, $r$ between 0.3 and 0.5=medium effect, $r$>0.5=large effect[28]). The binary logistic regression analysis was selected to explore the magnitude of the relative contribution of each game-related statistical parameter and the ability to predict winning from losing game outcomes. Binary logistic regression is robust to non-normal distributions of predictors, making it appropriate for the given dataset, where several predictors displayed non-normal distributions and because the dependent variable was binary[29]. Furthermore, binary logistic regression allows for the estimation of odds ratios, facilitating the interpretation of the effect of each predictor on the likelihood of a win. To avoid the issue of multicollinearity, bivariate Spearman correlations were used, and the predictors with correlation coefficients > 0.70 were flagged as potentially redundant and were removed from the analysis. The final model included 20 predictor variables covering various aspects of game-related performance variables, including shooting efficiency, rebounds, assists, and defensive statistics. All statistical analyses were completed with SPSS (Version 29.0; IBM Corp., Armonk, NY, USA), with the significance level set at $p<0.05$.

## Results

The Mann-Whitney U test compared the game-related performance variables between winning and losing teams. Descriptive statistics, test statistics, and effect sizes ($r$) for each variable are summarized in Table 1.

**Table 1**. Descriptive data (M±SD) for game-related statistical parameters between winning and losing teams

| Game-related statistics | Winning teams | Losing teams | Mann-Whitney U | p-value | Effect size (*r*) |
|---|---|---|---|---|---|
| **2P%** | 55.34 ± 8.38 | 50.18 ± 8.39 | 9330.50 | <0.001 | 0.30 |
| **3P%** | 38.46 ± 9.54 | 31.74 ± 8.48 | 8633.50 | <0.001 | 0.342 |
| **FT%** | 76.01 ±10.18 | 73.39 ± 10.75 | 12696.00 | 0.078 | 0.096 |
| **FG%** | 48.47 ± 5.72 | 42.57 ± 5.97 | 6751.50 | <0.001 | 0.456 |
| **eFG%** | 56.47 ± 7.57 | 49.28 ± 7.45 | 7538.00 | <0.001 | 0.438 |
| **TS%** | 61.28 ± 7.28 | 54.61 ± 7.72 | 8010.00 | <0.001 | 0.408 |
| **2PM** | 20.41 ± 4.35 | 17.93 ± 4.04 | 9762.50 | <0.001 | 0.274 |
| **2PA** | 37.00 ± 6.15 | 35.94 ± 6.37 | 12846.50 | 0.110 | 0.087 |
| **3PM** | 9.81 ± 3.07 | 8.22 ± 2.80 | 10484.00 | <0.001 | 0.231 |
| **3PA** | 25.50 ± 5.21 | 25.68 ± 5.36 | 13854.00 | 0.634 | 0.026 |
| **FTM** | 16.14 ± 5.19 | 14.47 ± 5.34 | 11383.50 | <0.001 | 0.176 |
| **FTA** | 21.41 ± 6.71 | 19.63 ± 6.39 | 11790.00 | 0.006 | 0.151 |
| **FGM** | 30.22 ± 4.07 | 26.15 ± 3.96 | 6736.50 | <0.001 | 0.458 |
| **FGA** | 62.50 ± 6.40 | 61.62 ± 6.14 | 13371.00 | 0.311 | 0.055 |
| **DEFREB** | 25.82 ± 4.22 | 22.60 ± 4.17 | 8358.50 | <0.001 | 0.36 |
| **OFFREB** | 11.17 ± 3.80 | 11.05 ± 4.02 | 14068.50 | 0.813 | 0.013 |
| **AST** | 20.01 ± 4.42 | 16.37 ± 4.27 | 8005.50 | <0.001 | 0.381 |
| **TO** | 12.60 ± 3.84 | 14.15 ± 4.02 | 11093.00 | <0.001 | 0.194 |
| **ST** | 7.35 ± 3.19 | 6.34 ± 2.73 | 11519.50 | 0.002 | 0.168 |
| **BLK** | 2.88 ± 1.85 | 2.23 ± 1.69 | 11275.00 | <0.001 | 0.185 |
| **PF** | 20.61 ± 3.53 | 21.60 ± 3.82 | 11739.50 | 0.005 | 0.154 |
| **PPG** | 86.40 ± 9.35 | 75.00 ± 9.59 | 5607.00 | <0.001 | 0.525 |
| **POSS** | 72.33 ± 4.74 | 72.28 ± 4.48 | 14148.00 | 0.882 | 0.008 |
| **ORTG** | 119.60 ± 11.90 | 103.92 ± 13.04 | 5403.50 | <0.001 | 0.538 |

**Note:** 2-point percentage (2P%), 3-point percentage (3P%), free-throw percentage (FT%), field goals percentage (FG%), effective fields goal percentage (eFG%), true scoring percentage (TS%), 2-point shots made (2PM), 2-point shots attempted (2PA), 3-point shots made (3PM), 3-point shots attempted (3PA), free-throws made (FTM), free-throws attempted (FTA), field goals made (FGM), field goals attempted (FGA), defensive rebounds (DEFREB), offensive rebounds (OFFREB), assists (AST), turnovers (TO), steals (ST), blocks (BLK), personal fouls (PF), points per game (PPG), possessions (POSS) and offensive rating (ORTG).
**Source**: The authors.

The analysis revealed significant differences in shooting efficiency metrics between winning and losing teams (Table 1). 2P%, 3P%, FG%, eFG%, and TS% showed statistically significant differences ($p<0.001$) with medium effect sizes, indicating that winners consistently outperform losers in these metrics. FT% did not show a significant difference ($p=0.078$), suggesting that free throw efficiency is less critical in determining match outcomes than other metrics. The largest effect size is observed in FG% ($r=0.456$), emphasizing the importance of overall field goal efficiency in winning games.

Winning teams significantly outperformed with small to medium effect sizes, losing teams in shot-making metrics, including FGM, 2PM, 3PM, FTM ($p<0.001$), and FTA ($p<0.05$).

However, no significant differences were found in FGA, 2PA, or 3PA, suggesting that shot-making ability, rather than shot volume, differentiates winning teams from losing ones (Table 1). Significant differences ($p<0.001$) between winning and losing teams were also recorded in AST, DEFREB, and TO, with a small to moderate effect size. Moreover, with a small effect size, ST and PF were statistically different ($p<0.05$). No significant difference was observed in OFFREB.

Moreover, PPG and ORTG showed statistically significant differences ($p< 0.001$) with large effect sizes, emphasizing the importance of offensive efficiency in determining match outcomes. On the other hand, POSS did not show a significant difference ($p=0.882$), suggesting that the number of possessions is not a key differentiator between winners and losers (Table 1).

A logistic regression analysis was conducted to assess the impact of the game-related performance metrics on game outcomes (win/lose). The model was statistically significant, $\chi^2(20)=255.120$, $p<0.001$, indicating that the predictors reliably distinguished between wins and losses. The model explained 70.7% of the variance in game outcomes (Nagelkerke $R^2=0.707$) and correctly classified 86.7% of cases.

As summarized in Table 2, the analysis yielded the following game-related statistics as significant predictors along with their B coefficients, p-values for testing whether a particular variable is significantly associated with the target variable, and odds ratios (exp B). Odds ratios (OR) indicate the amount of change expected in the log ratios when there is a 1-unit change in the predictor variable with all the other variables in the model held constant[30].

**Table 2**. Logistic regression game-related statistics and coefficients

| Analysis of maximum likelihood estimates | | | | | |
|---|---|---|---|---|---|
| **Game-related statistics** | **B (estimated coefficient)** | **Standard error** | **Wald Chi-Square** | **Sig.** | **Exp(B) (odds ratio-OR)** |
| **2PA*** | -0.399 | 0.189 | 4.433 | 0.035 | 0.671 |
| **OFFREB*** | 0.286 | 0.129 | 4.914 | 0.027 | 1.331 |
| **DEFREB**** | 0.397 | 0.057 | 48.173 | 0.001 | 1.488 |
| **ST**** | 0.468 | 0.084 | 30.894 | 0.001 | 1.596 |
| **BLK*** | 0.241 | 0.106 | 5.180 | 0.023 | 1.272 |

**Note**: *Statistically significant difference (p < 0.05), ** Statistically significant difference (p < 0.001).
**Source**: The authors

Among the predictors, ST is the strongest positive predictor of all variables ($B = 0.468$, $p < 0.001$, $OR = 1.596$), suggesting a 59.6% increase in the odds of winning per additional steal. Significant contributors included DEFREB ($B=0.397$, $p<0.001$, $OR=1.488$), indicating that each additional defensive rebound increases the odds of winning by 48.8%. Each additional OFFREB increases the odds of winning by 33.1% ($B = 0.286$, $p<0.05$, $OR= 1.331$), while BLK increases the odds of winning by 27.2% ($B =0.241$, $p<0.05$, $OR=1.272$). On the contrary, for each additional 2PA, the odds of winning decreased by 32.9% ($B = -0.399$, $p<0.05$, $OR=0.671$). This suggests that teams taking more two-point shots without converting them may be less likely to win.

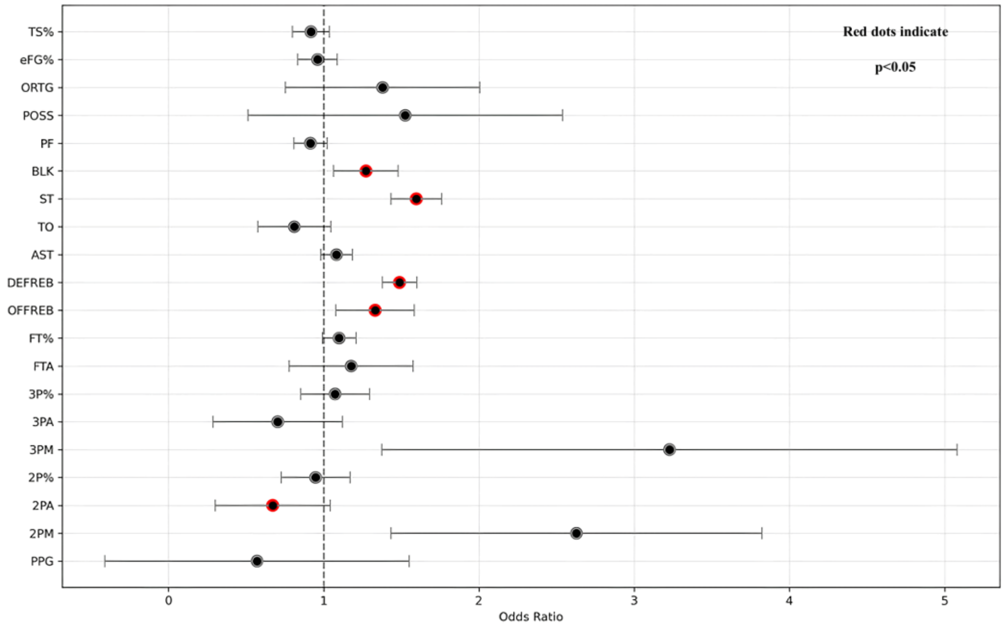


**Figure 1**. Odds Ratios with 95% Confidence Intervals
**Source**: The authors

Figure 1 presents the odds ratios (OR) and 95% confidence intervals (CIs) for the predictors in the logistic regression model. Significant predictors, including ST, DEFREB, OFFREB, BLK, and 2PA ($p < 0.05$), which suggest that they are the most important variables in predicting which team will win any game, are highlighted with red dots. Non-significant predictors included TS%, eFG%, ORTG, POSS, PF, TO, AST, FT%, FTA, 3P%, 3PA, 3PM, 2P%, and PPG.

## Discussion

The primary aim of this study was to identify game-related performance variables that differentiate winning and losing teams in the Basketball Champions League (BCL) and identify the most significant performance predictors of game outcomes.

The Mann-Whitney U test analysis revealed significant differences in shooting efficiency metrics, including 2P%, 3P%, FG%, eFG%, and TS%. Winning teams consistently outperformed losing teams in these metrics, emphasizing the importance of efficient shot-making as a key determinant of success. FG% and eFG% demonstrated the largest effect size, underscoring their critical role in distinguishing successful teams. These findings align with prior research[9,13,17,21] which identified shooting percentages, particularly FG% and eFG%, as decisive performance indicators.

The offensive efficiency is also expressed by PPG and ORTG and in the present study, both game-related statistics presented significant differences in favor of the winning teams. This observation supports the findings of Sampaio et al.[31] who emphasized that offensive efficiency, measured through metrics like ORTG, plays a decisive role in differentiating winning from losing teams. Furthermore, Cabarkapa et al.[9] highlighted the critical role of individual shooting skills, shot discipline, and collective decision-making in achieving offensive superiority. Three-point shooting has further shaped the performance gap between winning and losing teams. Although winners did not attempt more 3PA, they converted them at a higher percentage, demonstrating how efficiency from beyond the arc directly strengthens offensive output. This trend reflects the broader evolution of modern basketball, where the integration of the three-point shot into both set plays and transition opportunities has become central to offensive strategies. This tactical shift is reinforced by structured, teamwork-oriented offenses that consistently generate high-quality three-point opportunities[32]. The steady increase in three-point shooting and efficiency, coupled with greater specialization and comfort in long-range shooting, helps explain why winning teams sustain superior offensive efficiency metrics, particularly in ORTG, FG%, and eFG%, compared to their losing counterparts[33].

Shot-making metrics such as FGM, 2PM, 3PM, and FTM also exhibited significant differences ($p<0.001$), with small to medium effect sizes, while shot volume metrics, including FGA, 2PA, and 3PA, did not. This supports the argument that shot efficiency is more critical than volume, as teams that excel in converting scoring opportunities into successful attempts are more likely to win[4,13,17,23].

Rebounding also played a crucial role in differentiating winning teams, with significantly higher DEFREB recorded for winners. This finding aligns with previous studies[17.34,24], which identified DEFREB as a key parameter for success. Teams that demonstrate tactical discipline in boxing out and securing DEFREB limit second-chance points for opponents, increasing their chances of victory[9,19]. Conversely, no significant differences were observed in OFFREB, consistent with mixed findings in the literature. While some studies[9,35] reported a significant impact of OFFREB on game outcomes, others did not[1,8]. Additionally, defensive plays, including ST and BLK, emerged as significant differentiators between winning and losing teams. This observation corroborates findings from prior studies[7,9,21,35,36], which demonstrated that winning teams had superiority in the defensive-related game statistics. These metrics disrupt opponents' offensive flow and create additional scoring opportunities, particularly when steals occur far from the opponent's basket[37]. Greater BLK numbers also indicate superior rim protection[9].

Importantly, defensive-related variables, such ST, BLK, and DEFREB, proved decisive variables in distinguishing winning and losing teams. Their impact extends beyond denying opponents' scoring opportunities, as they directly increase possession time, limiting opponents' scoring chances and allowing teams to initiate transition opportunities, thereby increasing offensive efficiency. These results suggest that winning teams are not only more efficient in converting their possessions but also more effective in regaining or extending possessions through defensive disruptions, highlighting the importance of developing effective rebounding skills and defensive schemes designed to create distractions.

According to the study's results, AST and TO significantly differentiated winning teams, highlighting their superior teamwork and ball distribution[14,19]. Winning teams exhibited fewer TO and more AST, reflecting better decision-making, cohesion, and offensive efficiency[6,16]. This finding supports the notion that minimizing turnovers and maintaining possession is critical for success[1,7].

Winning teams committed slightly fewer PF ($p<0.05$), limiting FTA and FTM opportunities for opponents. Managing fouls effectively allows teams to maintain defensive intensity without risking foul trouble for key players. This aligns with previous findings that winning teams control their fouls better, reducing opportunities for opponents to score through free throws[7,19].

The logistic regression analysis reinforced the importance of defensive metrics, with ST and DEFREB emerging as the strongest predictors of winning in BCL games. Each additional ST increased the odds of winning by 59.6%, and each additional DEFREB by 48.8%. Although OFFREB and BLK also contributed, their effect sizes were smaller, highlighting that ST and DEFREB are more impactful in predicting game outcomes.

Interestingly, 2PA negatively predicted winning odds, with each additional attempt reducing the likelihood of victory by 32.9%, a finding that aligns with the results of Karipidis et al.[2] and Trninić et al.[19]. This finding underscores the importance of efficiency over volume, particularly as modern basketball increasingly emphasizes high-efficiency shots, such as three-pointers or attempts close to the basket[38]. Poor shot selection, a characteristic of losing teams, reflects lower tactical discipline and a lack of effective decision-making under defensive pressure[19]. Rather than directing that teams should avoid mid- or short-range shots altogether, this result reveals how defensive pressure limits opponents' ability to generate high-quality three-point or paint opportunities, forcing them into contested two-point attempts with lower efficiency. In modern basketball, where spacing and three-point accuracy play central roles, defensive schemes that push opponents into worse-positioned and pressured two-point shots may represent an indirect but highly impactful determinant of success.

Previous research provides varying insights into performance predictors. A study by Buyukcelebi et al.[35] identified DEFREB and ST as the most important defensive metrics for success, followed by BLK and OFFREB, which is consistent with this study. Other research[1,21,24,37] similarly highlighted DEFREB as a key factor, while ST emerged as a critical performance indicator in elite competitions due to its ability to disrupt possessions and generate scoring opportunities[21]. Offensive factors such as FG% and AST have also been shown to play pivotal roles in success, as noted by Mikołajec et al.[16] and Cabarkapa et al.[1]. These studies highlighted that, alongside DEFREB, offensive metrics like FG% and AST significantly discriminate winners from losers. Özmen[18] also identified turnovers as a key determinant, further supporting the notion that reducing TO and maintaining possession is critical for success.

The decline between the results of the Mann-Whitney U test and the logistic regression in some performance variables can be attributed to differences in the purpose, methodology, and statistical assumptions of these analyses. The Mann-Whitney U test highlights broad differences between groups, often driven by statistical rather than practical significance. In contrast, logistic regression identifies variables that meaningfully predict game outcomes while adjusting for interactions and shared influences among predictors. This methodological distinction explains why some variables decline in significance when transitioning from univariate to multivariable analyses[39].

However, the limitations of this research must be recognized. First, the complexity of basketball games is influenced by numerous factors, including player skills, game locations, team strategies, coaching decisions, injury status, and other external variables. These elements were not incorporated into the present analysis, potentially constraining the scope of the findings. Future studies should account for these variables to provide a more comprehensive understanding.

The findings of this study contribute to the existing body of literature, reinforcing the multifaceted nature of performance in basketball, and have important implications for coaches, analysts, and teams aiming to optimize performance. First, defensive metrics, particularly ST and DEFREB, stand out as the most decisive predictors. Teams should emphasize defensive rebounding drills, pressure, and turnover creation to disrupt opponents' scoring opportunities. Second, while shot volume is important, shot efficiency is the key differentiator between winning and losing teams. Teams should focus on converting their opportunities rather than simply increasing the number of attempts. Improving shooting efficiency, particularly FG% and eFG%, should be a priority for teams aiming to increase their chances of winning.

## Conclusion

This study highlights the critical performance variables differentiating winning and losing basketball teams. Defensive performance, particularly DEFREB, ST, and BLK, played a crucial role in predicting game outcomes, while 2PA negatively predicted the odds of winning. Moreover, offensive efficiency metrics, including ORTG, FG%, eFG%, and TS%, emerged as significant determinants of success, emphasizing the importance of shot-making ability. Overall, these findings underscore that the winning frame in BCL combines high offensive efficiency (expressed through ORTG and shooting percentages) with defensive actions that recover possession, restrict efficient three-point shooting, and defensive schemes designed to force opponents into low-quality, pressured two-point attempts.

These results provide valuable insights into the performance metrics contributing to game success and highlight the importance of defensive performance and offensive efficiency. Researchers can develop targeted interventions to enhance training methodologies and team performance by identifying key performance indicators that distinguish winning from losing teams.

Future research should explore the underlying factors contributing to the negative association between two-point attempts and game outcomes. Additionally, studies examining team strategies, player-level performance, and other situational variables could provide further insights into optimizing game performance.

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**CRediT author statement**

Panagiotis Foteinakis: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing
Stefania Pavlidou: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing – review & editing

**ORCID**:
Panagiotis F. Foteinakis: https://orcid.org/0009-0001-4999-5008
Pavlidou P. Stefania: https://orcid.org/0009-0007-3862-9348

**Editor**:Jorge Both.
Received on Jan 03, 2025.
Reviewed on Aug 17, 2025.
Accepted on Aug 18, 2025.

**Corresponding author**: Panagiotis F. Foteinakis, pfotinak@phyed.duth.gr