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# Changes in Defensive Variables Determining Success in the NBA over the Last 10 Years

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**Abstract:** This study aimed to determine changes in defensive strategies over the past decade in the National Basketball Association (NBA) and identify the most crucial factors for winning games. The study analyzed all games where the 30 NBA teams played over 11 seasons (13,530 games) and created outcome statistics based on win–loss records. Five defensive variables (OREB [offensive rebound], DREB [defensive rebound], TREB [total rebound], ST [steal] and BLK [block]) were compared, revealing that OREB ($p < 0.03$), DREB ($p < 0.001$), TREB ($p < 0.001$), ST ($p < 0.001$) and BLK ($p < 0.001$) occur significantly in winning teams. Also, it has been observed that the changes over the years in the variables OREB ($p < 0.01$), DREB ($p < 0.01$), TREB ($p < 0.01$) and ST ($p < 0.01$) are statistically significant. However, there was no significant difference in the BLK variable over the years ($p = 0.24$). The impact of defensive variables on winning and their factor loadings are as follows: DREB ($\lambda = 0.50$), ST ($\lambda = 0.15$), TREB ($\lambda = 0.10$), BLK ($\lambda = 0.08$) and OREB ($\lambda = 0.06$). Coaches can use these findings on defensive variables to strategize and counter opponents during games.

**Keywords:** basketball; analysis; NBA; defense; team performance



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## 1. Introduction

Basketball is one of the most popular sports globally, fostering intense competition and a strong desire to win. Players' fitness levels, anthropometric characteristics, technical skills and coaches' tactical strategies can determine success in this competitive arena [1]. Like other sports, basketball coaches utilize notational analysis to enhance team and player performance and readiness for competition [2–4]. The recent surge in research on performance analysis in basketball can be attributed to the intensifying competition and pursuit of success in sports [5,6]. This trend has yielded positive outcomes for training and competition protocols. Moreover, leveraging analytical data to prepare for competitions at the highest standards can favor players' technical, tactical, physical, psychological and physiological attributes [7].

In-game performance indicators in basketball are used to evaluate the form status of players and teams [8]. If these performance indicators are chosen well, it helps coaches objectively assess excellent or bad performances [2,9]. Owing to the positive feedback in this area, sports scientists have conducted various studies on this subject [1,10]. With an increase in studies, the interest of coaches and players in the analysis has grown. The increased interest in analysis can also be understood from the importance of in-game statistics [11–13].

In studies conducted on basketball analysis, performance indicators affecting winning or losing have been revealed using different statistical data [14–16]. Previous studies have investigated the effects of defense performance indicators on winning games. In the analysis of 53 national team matches, it has been reported that defensive rebounds from two-point and three-point shots, as well as missed three-point shots are significant parameters influencing teams' winning and losing outcomes [17]. In a study examining the variation of performance indicators according to players' gender and competitive level, it was determined that shooting attempts, free throws, defensive and offensive rebounds, blocks, steals and assists are significant in-game performance parameters [18]. In a study conducted to determine the performance indicators between winning and losing teams in the Spanish basketball league, home teams were found to be superior in two-point shots (structural coefficients [SC] = 0.40), assists (structural coefficients [SC] = 0.41) and defensive rebounds (structural coefficients [SC] = 0.36) in the competitions they won [19]. In competitions won by away teams, it was determined that there were differences in the parameters of assistance and steals [19]. Apart from these studies, there are a relatively limited number of retrospective studies showing the changes in in-game parameters in basketball over the years. Identifying changes in in-game parameters can provide clues about the direction of trends in the game. Therefore, this study is significant for determining the direction of change in defensive parameters in games.

Other studies investigating the indicators of winning and losing in basketball and exploring defensive performance indicated that defensive rebound, offensive rebound and block variables influence the outcome of the game (DR SC = 0.65, OR SC = 0.63, BLK SC = 0.58) [20]. Researchers have suggested that another vital indicator distinguishing between winning and losing teams is block (SC = 0.25) [21]. In addition, it was found that teams with higher average offensive rebounds also had increased performance in the same direction ($p < 0.05$) [10]. When the studies examined the pace of game statistics, the game speed in the NBA was above the average in European leagues [14]. The increase in the number of offenses increases the number of actions in the game. The International Basketball Federation (FIBA) changed this rule in 2000, as it was thought that an increase in offense and action would positively affect the game's attractiveness. The shot clock time limit was reduced from 30 s to 24 s. In addition, the time it took to advance the ball across midcourt was reduced from 10 s to 8 s and after taking the offensive rebound on 1 October 2014, the shot time started with the 14 s time limit. All of these changes were carried out to increase the speed of play and the number of offenses that would increase the game's attractiveness. The changes made to increase the pace of play increased the number of actions within the game. As the number of offensive actions increases, the number of defensive variables is also expected to increase accordingly (e.g., rebounds, steals and blocks).

In addition to these factors, defensive strategies in basketball can vary based on matchups and responses to offensive tactics. Therefore, the variables involved in defense can change depending not only on player profiles and tactical approaches but also on the strategies employed by the offense. In this sense, the ability of offensive methods to influence defensive strategies in different directions is one of the elements that make establishing an appropriate defensive setup challenging.

Changes in game rules, player profiles, skill levels and tactical diversity in the NBA over the years suggest potential variations in the in-game statistics. Therefore, this study hypothesized that the numerical averages of the defensive variables and their effects on the outcome of the competition would have increased over the years. This study also aimed to assess game rules, player profiles and game speed changes over time. This study aimed to understand how these factors have affected defensive statistics in NBA competitions over the past decade. Additionally, this study aimed to determine the significance of these variables with competition outcomes.

## 2. Materials and Methods

### *2.1. Research Design*

The study was conducted using a causal comparison design, one of the quantitative research methods. Causal comparison design enables the determination of the differences in the study population with cause and effect relationships without any intervention [22].

### *2.2. Research Scope*

The study focused on games played in the NBA league in different years, with a sample drawn from NBA games between 2008 and 2019. The study included data from 30 teams that competed in the NBA league during the 2008–2019 seasons. The research data spanned 11 seasons and included 660 data points on defensive variables.

### *2.3. Data Collection Tool*

The study data ($n$ = 660) obtained from the NBA league for 11 seasons were accessed through the official website of the NBA (https://www.nba.com/stats, accessed on 12 May 2023). The {rvest} package of the R (Core Team) programming language was used to extract the data.

### *2.4. Data Extraction and Processing*

After the study data were collected with the R programming language, they were transferred to the Excel (ver. 16.37, Microsoft Corporation, Redmond, WA, USA) environment. The data are coded according to seasons and win–lose status. The mean of defensive variables (offensive rebound, defensive rebound, total rebound, steal, block) for each team in wins and losses were recorded. Detailed information on the obtained data was presented with the Open Science Framework.

### *2.5. Statistical Analysis*

The data of this study were analyzed in two stages. In the first stage, hypothesis tests were applied to determine the defensive variables affecting the win–loss situation. The results were reported as arithmetic mean and standard deviation (mean $\pm$ SD). The normal distribution of the data was checked using Kolmogorov–Smirnov analysis. Since the data were not normally distributed, the effect of defensive variables on the game result was evaluated by Mann–Whitney U analysis. On the other hand, the Kruskal–Wallis H test was applied to analyze the change in defensive variables over the years. The percentage change of defensive variables in the case of wins and losses was calculated using the following formula: ([average of wins$-$average of losses]/average of losses) $\times$ 100. Effect sizes (ES) were determined with Cohen's d and interpreted according to the following reference values: (<0.2) = trivial, (0.2–0.6) = small, (0.6–1.2) = moderate, (1.2–2.0) = large, (2.0–4.0) = very large and (>4.0) = extremely large [23]. The SPSS 22.0 (IBM SPSS Statistics, Inc., New York, NY, USA) package program was used to compare groups. Effect sizes were calculated with the {effsize} package of the R 4.2.2 (Core Team) programming language. The statistical significance level was accepted as $p < 0.05$ in all analyses.

In the second stage, machine learning algorithms were used to predict the most critical defensive variable affecting the winning situation in the NBA basketball league. A dataset containing five attributes (offensive rebound, defensive rebound, total rebound, steal, block) and 660 samples were used for the analysis. The attributes were determined to predict the most critical defensive variable affecting the winning situation. Detailed information about the defensive variables and definitions used in this study can be found in Table 1. The data is divided into 70% training and 30% test data to predict the most critical defensive variable in the win state with machine learning algorithms. This method is aimed at the analysis program to learn the data and make predictions based on these data. Then, the training data was repeated 10 times with five layers of cross-validation and machine learning algorithm models were created. The success of the algorithm models was evaluated based on the test data and reported in terms of accuracy, precision, sensitivity and F-1 score. Defensive variables are categorized into two categories (wins and losses) in this study and the most critical defensive variable is predicted for wins. Since the study involves a classification problem (i.e., win–loss situation), six machine learning algorithms (XGBoost, logistic regression, random forest, Gaussian Naive Bayes, K-Nearest Neighbors, support vector machine) were preferred in similar studies [24–26]. Therefore, this study also used the same algorithms.

**Table 1.** Characteristics of the variables used to estimate the defensive variables that affect the game result.

| Variable Abbreviation | Variable Name | Definition |
|---|---|---|
| team | Teams | It expresses the defensive variable averages of the teams in case of wins and losses. |
| game_result | Game Result | The dependent variable of the study defined as wins and losses. |
| off_rebound | Offensive rebound | Number of rebounds received by the attacking team as a result of a missed shot. |
| def_rebound | Defensive rebound | The number of rebounds received by the defending team as a result of a missed shot. |
| tot_rebound | Total rebound | The total of the current rebounds captured by the players while on the field. |
| steal | Steal | Gaining position by intercepting a pass or grabbing a ball that is in the control of the opposing player. |
| block | Block | When a defensive player legally deflects a field goal attempt from an offensive player to prevent a score. |

Among the algorithm models created, the most successful prediction method was the XGBoost (eXtreme Gradient Boosting) algorithm and the most critical defensive variable for the win was determined with the XGBoost algorithm. The {xgboost}, {caret}, {class}, {randomForest}, {e1071} and {Rfast} packages of the R 4.2.2 (Core Team) programming language were used for the analysis with machine learning algorithms.

## 3. Results

A total of 660 data points were included in this study, with no data loss observed. The hypothesis test results indicated statistically significant findings regarding defensive variables about wins and losses in the NBA league. The impact of defensive rebounding on game outcomes regarding wins and losses was assessed, revealing a moderate effect favoring wins (ES = 1.39, [95% CI = 1.22–1.56], $p < 0.001$). Specifically, defensive rebounding increased by 12% in the case of a win. Similar results were observed for total rebounds, which had a moderate effect on wins, showing an increase of 8% (ES = 1.51, [95% CI = 1.34–1.69], $p < 0.001$). Conversely, there was a 11% increase in the number of steals in the event of a win, with this increase having a small effect on the win (ES = 0.67, [95% CI = 0.49–0.80], $p < 0.001$). The block performance of teams was also found to have a small effect on winning games, with the number of blocks increasing by 17% in case of a win. In contrast to other defensive variables, offensive rebounding increased by 1.93% in the event of a loss, with this variable showing an insignificant effect on losses (ES = −0.14, [95% CI = −0.29–0.01], $p = 0.03$). Detailed information on the impact of defensive variables on game results is presented in Table 2.

**Table 2.** Comparison of defensive variables in game win versus game loss.

| Variables | Winner ($n$ = 330) (Mean ± SD) | Loser ($n$ = 330) (Mean ± SD) | Comparison within Group ($p$-Value) | Percent Change (%) | ES Cohen-D (95% CI) | ES (Interpretation) |
|---|---|---|---|---|---|---|
| Offensive rebound | 10.7 ± 1.50 | 11 ± 1.40 | 0.03 * | −2 ↓ | −0.14 (−0.30–0.01) | Trivial |
| Defensive rebound | 33.8 ± 2.8 | 30.1 ± 2.40 | 0.001 * | 12 ↑ | 1.39 (1.20–1.60) | Moderate |
| Total rebound | 44.5 ± 2.40 | 41 ± 2.20 | 0.001 * | 8 ↑ | 1.51 (1.30–1.70) | Moderate |
| Steal | 8 ± 1.20 | 7.3 ± 1.20 | 0.001 * | 11 ↑ | 0.67 (0.50–0.80) | Small |

**Table 2.** *Cont.*

| Variables | Winner ($n$ = 330) (Mean ± SD) | Loser ($n$ = 330) (Mean ± SD) | Comparison within Group ($p$-Value) | Percent Change (%) | ES Cohen-D (95% CI) | ES (Interpretation) |
|---|---|---|---|---|---|---|
| Block | 5.3 ± 0.90 | 4.5 ± 0.80 | 0.001 * | 17 ↑ | 0.86 (0.70–1.00) | Small |

Note. * $p$ < 0.05; ES: Effect size; SD: Standard deviation; 95% CI: 95% confidence interval; ↑: Increase; ↓: Decrease.

When the impact of defensive variables on the game's outcome was analyzed based on different years, it was discovered that all variables directly influenced the game's win except for offensive rebounding (see Figure 1a–e). Also, it was concluded that offensive rebounding has exhibited an upward trend in contributing to game wins in recent years. Information details regarding the influence of defensive game variables on game results over the years are presented in Figure 1a–e and Table 3.

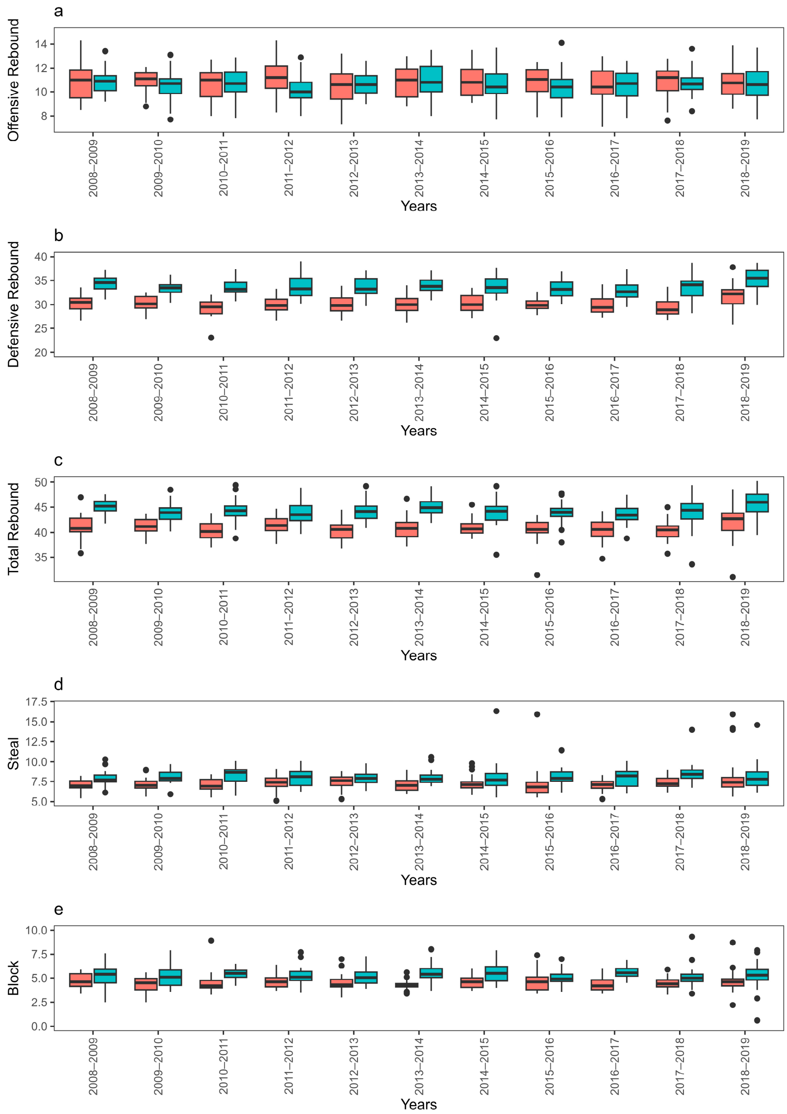


**Figure 1.** (**a**–**e**) The effect of defensive variables on game results by years. Note. The green color defines win and the red color indicates loss; (**a**) Comparisons of offensive rebound variable based on win–loss situation according to seasons; (**b**) Comparisons of defensive rebound variable based on win–loss situation according to seasons; (**c**) Comparisons of total rebound variable based on win–loss situation according to seasons; (**d**) Comparisons of steal variable based on win–loss situation according to seasons; (**e**) Comparisons of block variable based on win–loss situation according to seasons. Note. The black dots indicate outliers.

**Table 3.** Results of descriptive characteristics and assessment of defensive variables by years.

| Defensive Variables | 2008–2009 | 2009–2010 | 2010–2011 | 2011–2012 | 2012–2013 | 2013–2014 | 2014–2015 | 2015–2016 | 2016–2017 | 2017–2018 | 2018–2019 | Kruskal Wallis H Test ($df$) = $\chi 2$, $p$-Value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Offensive rebound | 11.1 ± 1.00 | 11 ± 1.10 | 10.9 ± 1.30 | 11.3 ± 1.40 | 11.2 ± 1.40 | 12.9 ± 10.90 | 11 ± 1.00 | 10.4 ± 1.10 | 10.1 ± 1.30 | 11.7 ± 1.20 | 10.4 ± 1.10 | (10) = 90.83, 0.01 * |
| Defensive rebound | 30.3 ± 2.20 | 30.80 ± 2.30 | 30.5 ± 2.30 | 30.6 ± 2.40 | 31 ± 2.20 | 31.1 ± 4.40 | 32.5 ± 2.20 | 33.3 ± 2.20 | 33.4 ± 2.30 | 33 ± 4.70 | 34.9 ± 2.50 | (10) = 175.38, 0.01 * |
| Total rebound | 41.4 ± 2.20 | 41.8 ± 2.40 | 41.4 ± 2.50 | 42.1 ± 2.60 | 42.2 ± 2.30 | 42.3 ± 3.30 | 43.3 ± 2.40 | 43.8 ± 2.40 | 43.5 ± 2.60 | 43 ± 3.20 | 45.2 ± 2.80 | (10) = 98.33, 0.01 * |
| Steal | 7.2 ± 0.90 | 7.2 ± 1.10 | 7.3 ± 0.10 | 7.6 ± 1.00 | 7.7 ± 0.90 | 8 ± 1.80 | 8 ± 1.10 | 9 ± 8.60 | 7.7 ± 0.80 | 8 ± 1.40 | 7.9 ± 1.90 | (10) = 38.28, 0.01 * |
| Block | 4.80 ± 0.90 | 4.90 ± 0.80 | 4.8 ± 1.00 | 5.1 ± 0.90 | 5.10 ± 1.00 | 4.8 ± 1.00 | 5.4 ± 5.00 | 5 ± 1.00 | 4.8 ± 0.80 | 5 ± 1.20 | 5 ± 0.80 | (10) = 12.66, 0.24 |

Note. This table indicates the statistical significance of the 10-season change in defensive variables. If the Kruskal–Wallis H test results showed $p < 0.05$, it was concluded that the defensive variables' match averages differed significantly over the 10 seasons. Descriptive statistics are given as mean ± standard deviation; *: $p < 0.05$.

In addition to hypothesis testing, six machine learning algorithms were used to forecast the impact of defensive variables on game outcomes in the NBA league. The XGBoost algorithm emerged as the most effective model in predicting the defensive variables influencing game results, achieving an accuracy rate of 86%. Conversely, the logistic regression algorithm exhibited the lowest predictive accuracy at 81%. The F1 scores and accuracy rates were comparable, suggesting consistent results. Detailed information on the success rates of the algorithm models is presented in Table 4.

**Table 4.** Prediction success of machine learning algorithm models.

| | **XGBoost (95% CI)** | **Logistic Regression** | **Random Forest** | **Guassian Naive Bayes** | **K-Near Nearbors** | **Support Vector Machine** |
|---|---|---|---|---|---|---|
| Accuracy | 0.86<br>(0.83 to 0.88) | 0.81<br>(0.78 to 0.83) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.83<br>(0.80 to 0.85) |
| Precision | 0.87<br>(0.84 to 0.89) | 0.81<br>(0.78 to 0.83) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.83<br>(0.80 to 0.85) |
| Recall | 0.86<br>(0.83 to 0.88) | 0.81<br>(0.78 to 0.83) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.83<br>(0.80 to 0.85) |
| F1 score | 0.86<br>(0.83 to 0.88) | 0.81<br>(0.78 to 0.83) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.84<br>(0.81 to 0.86) | 0.83<br>(0.80 to 0.85) |

Note. 95% CI: Confidence interval upper and lower limits.

The XGBoost algorithm estimated the most crucial defensive variable influencing game wins in the NBA league. The results obtained with the XGBoost algorithm were consistent with the hypothesis tests, revealing that defensive rebounding is the most significant defensive factor impacting game wins, with an accuracy rate of 86%. Detailed information about the defensive variables affecting the game win is presented in Figure 2.

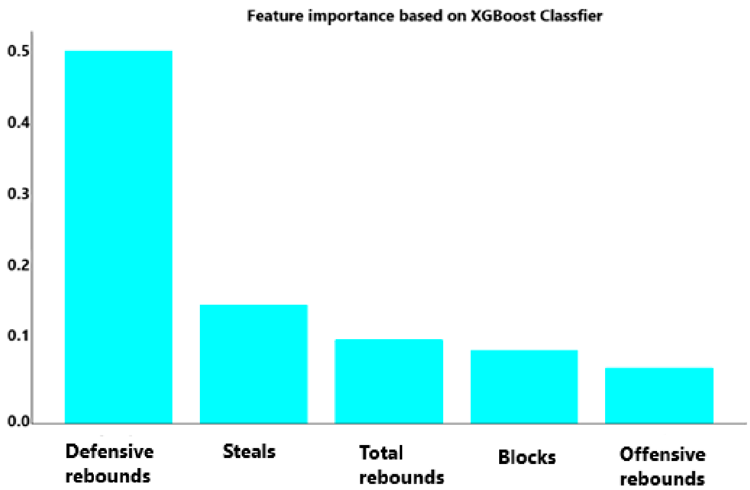


**Figure 2.** The effect of defensive variables on game results by years. Note. Numerical values on the y-axis represent the factor loading of the relevant defensive variable. Factor loading was used to indicate the importance of a variable in this model.

The defensive variable with the highest factor loading and the most significant impact on winning was DREB ($\lambda$ = 0.50), while the variable with the least impact on was offensive rebounds ($\lambda$ = 0.06). Additionally, the impact of other defensive variables on winning and their factor loadings are as follows: ST ($\lambda$ = 0.15), TREB ($\lambda$ = 0.10) and BLK ($\lambda$ = 0.08).

## 4. Discussion

Our study examined the significance of defensive variables in NBA competition between 2008 and 2019. The evolution of these variables over the years was also analyzed.

Previous research has suggested that defensive performance indicators underscore the importance of the variables discussed in this study [27–29]. Many studies have explored the defensive and offensive variables. Our study sought to assess fluctuations in the defensive aspects of a game over a decade. Furthermore, it aimed to ascertain how the impact of these variables on competition outcomes changed over time.

The findings indicate a notable increase in offensive rebounding among winning teams in recent years, which significantly affects game outcomes. Moreover, there was a significant shift in the influence of offensive rebounding on the competition results over time ($p < 0.05$). However, this was not identified as the primary determinant of winning or losing teams. Previous research has presented conflicting results, according to the results of this study. A study examining performance indicators that distinguish winning and losing teams emphasized that offensive rebounds are a crucial defensive factor affecting game outcomes [30]. The disparities in findings can be attributed to the timing of the study, which was conducted before the implementation of new rules aimed at accelerating gameplay and was based on data from a single season. A study investigating dynamic models for evaluating team performance in the Basketball World Cup has identified that the number of offensive rebounds can significantly impact game outcomes [31].

In addition to examining the impact of offensive rebounds on the game, certain studies have delved into the individuals responsible for securing the rebounds. A study conducted in Spain aimed to identify the determinants of offensive rebound performance among elite basketball players [32]. Researchers suggest a direct correlation between players' positions and their success in securing offensive rebounds [32]. The discrepancies between the findings of this study and previous research can be ascribed to various factors, such as the retrospective nature of the data evaluation, the simultaneous consideration of different seasons in the analysis and the emphasis on regular season statistics.

The findings indicated that defensive rebounding had a moderate impact on the game's outcome regarding wins and losses, favoring wins (ES = 1.39, [95% CI = 1.22–1.56], $p = 0.01$). Furthermore, defensive rebounding increases by 12% in the case of a win. Moreover, there was a significant change in the influence of defensive rebounding on the game's outcome over time ($p < 0.05$). Based on these results, defensive rebound is crucial in determining the outcome of competition. This conclusion is consistent with those of previous studies. For instance, a study examining performance indicators that distinguish winning and losing teams in the Spanish Basketball League identified defensive rebounds as a critical variable affecting game outcomes [27]. Similarly, there are studies highlighting the significant impact of defensive rebounds on basketball success [33]. A study examining critical in-game variables for winning in the Spanish Basketball League, Portuguese Basketball League and NBA emphasized the importance of defensive rebounds in achieving victory [28]. This study also investigates the influence of total rebound on competition outcomes. Alongside these data, the total number of rebounds also demonstrated similar outcomes, indicating a moderate effect on the game's outcome with an 8% increase in the likelihood of winning (ES = 1.51, [95% CI = 1.34–1.69], $p = 0.01$). Furthermore, there was a significant change in the impact of the total rebound on game results over the years ($p < 0.05$). Previous literature has typically analyzed defensive and offensive rebounds separately rather than considering total rebounds. In contrast to prior research, this study identifies significant performance indicators in the game and highlights their significance levels. Rebounding can be viewed as a team accomplishing its defensive objective; however, it is not solely indicative of defensive success, but also creates opportunities for fast breaks. Teams that swiftly transition to offense following a rebound gain an advantage by capitalizing on unprepared opponents before establishing defensive matchups. Therefore, increasing the number of rebounds can be interpreted as defensive success and offensive opportunity.

Individual and team defense efforts in basketball games cause turnover. Opponent turnover does not happen only by waiting for a personal mistake, but also by stealing the ball with concentration, quickness and vision. Ability to steal is a defensive factor that distinguishes players. Therefore, studies supported by statistical data show that stealing is one of the most critical indicators of variable use. When the findings of the study were analyzed, it was found that there was an 11% increase in the number of steals in case of a game win and this increase had a small effect on the win (ES = 0.67, [95% CI = 0.49–0.80]). The results of our study are similar to those of previous studies. Similar studies have indicated that a study conducted in the NBA highlighted the necessity of the steals variable for success in competition [34]. Another study investigating success attributes among basketball teams found that the average number of steals was significantly different from other teams [13]. A study analyzing key performance indicators between winning and losing teams in under−16 basketball matches demonstrated that winning teams had a higher rate of steals compared to losing teams [10]. While steal statistics represent individual defensive performance, they are also influenced by team-based defensive tactics such as double teams and full-court pressure. Moreover, teams that steal the ball transition quickly to the opponent's half and disrupt their offensive rhythm.

The block variable is a crucial factor that influences the outcomes of basketball games. This study showed that teams' performance in blocking plays has a minor impact on game results, with a reported increase of 17% in the number of blocks in winning games. The limited effect of blocking on game outcomes can be attributed to the increasing difficulty of blocking shots as offensive speed and distance shots increase. Moreover, the study indicates that the influence of the block variable on game results has remained relatively stable over the years ($p > 0.05$). There are studies that identify blocks as an important performance indicator for winning games [35]. Furthermore, performance indicators in the Spanish Basketball League from 2003 to 2013 have been analyzed, highlighting the significance of the blocks variable in game outcomes [15]. Comparisons of variable usage in Major League Baseball and the NBA have suggested that the blocks variable plays a role in determining game outcomes [36]. Since blocking thwarts opponents' scoring attempts, it is considered a defensive parameter that directly hinders scoring. Furthermore, a successful block reflects attributes such as effort and determination and sends a psychological message to the opponent.

Over time, fluctuations in various defense metrics can offer valuable insights into sports. The notable disparities in rebound averages witnessed across different periods can be attributed to the greater number of shot attempts. Moreover, escalation in shot attempts will likely contribute to increased rebound and successful shots. Given that the fundamental aim of the game is to score points on offense and hinder the opponent from scoring on defense, the accelerated pace of play and heightened activity could lead to variations in statistical categories, such as steals and blocks.

The statistical variances observed cannot be solely attributed to alterations in game speed and the frequency of actions. Moreover, modifications in coaching strategies and training methodologies at the collegiate level, as well as the application of principles such as defensive positioning and mobility, are more prominently demonstrated by players. The confluence of numerous factors signifies a rise in player activity and advancement and can also be construed as a progression in the sport itself.

The present study is subject to certain limitations that warrant consideration in future research. These limitations stem from the absence of classification based on teams' defensive ratings, the lack of categorization based on player profiles and the restricted number of accessible variables (such as the number of fouls, technical fouls, defensive tactics, player rotations, etc.). Additionally, the study exclusively analyzed statistics from the NBA, excluding games from European leagues with varying durations that could influence the frequency of actions. Nevertheless, exploring data on defensive and offensive variables from international competitions organized by the FIBA could be a potential avenue for future research.

## 5. Conclusions

Our study uncovered the evolution of defensive variables in the NBA over the years, a finding corroborated by similar studies in the literature. Coaches can proactively adjust their strategies in response to the changing defensive landscape. Additionally, the study highlighted the significance of data in informing coaching decisions during games. When utilizing such data, coaches and sports scientists must comprehensively understand their athletes' strengths, skills and physical constraints. Furthermore, this study examined the evolution of defensive variables over time, which can offer coaches valuable insights into the changing sports trends. Effective defense necessitates intense focus, physical conditioning, individual proficiency and cohesive teamwork. The various factors highlighted in the research should be viewed comprehensively. It is recommended that coaches who adapt their players to the evolving dynamics of the sport are more likely to attain success. The paper presents findings on the progression of these variables over 10 years. The data presented in the results, corroborated by prior research, can significantly influence the teams' expectations, strategies and training methodologies. This data is adaptable to various organizations, teams and leagues.

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