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KEY PERFORMANCE INDICATORS OF SUCCESS IN NCAA WOMEN'S COLLEGE BASKETBALL

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KEY PERFORMANCE INDICATORS OF SUCCESS IN

NCAA WOMEN'S COLLEGE BASKETBALL

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Abstract

Despite analysis of key performance indicators (KPIs) in men's and professional basketball, comparable research in women's college basketball remains limited. This gap persists even with the unprecedented growth and increased visibility of the women's game in recent years. This study addresses this imbalance by examining box score data from an NCAA Power 4 conference between the 2021-25 seasons.

Using an adaptation of Dean Oliver's Four Factors framework, three KPIs associated with winning were identified: effective field goal percentage (eFG), rebounding margin (REBMARG), and turnover margin (TOMARG). Results indicated that a one-unit increase in turnover margin corresponded to a 74.3 percent increase in the odds of winning a given game.

For a specific Power 4 program, conditional inference trees (CITs) revealed a unique combination of KPIs that maximized winning. A distinct combination of points and personal fouls were associated with a 97.3 percent winning percentage. Collectively, these findings provide a foundation for developing a data-driven game model to achieve sustained success in the NCAA women's college basketball landscape.

Keywords: key performance indicators, NCAA, sports performance, women's basketball

CHAPTER 1. INTRODUCTION

The 2025 NCAA Women's Basketball Tournament recorded its second-highest viewership in history, demonstrating the unprecedented growth of the women's game in recent decades. The tournament generated 8.5 billion viewing minutes across ESPN networks, and viewership for Elite Eight games rose by 34 percent compared to 2024. Together, these figures underscore the significant rise in public interest surrounding women's basketball in recent years (NCAA, 2025). Despite rapid growth in popularity and financial stakes, women's basketball has received comparatively limited attention in sports analytics research, which has historically focused on the men's game. There is an unmet need to identify key performance indicators (KPIs) associated with success in women's basketball, and these insights can help basketball programs develop more effective technical and tactical advantages.

This is particularly important in women's basketball, where the sport remains structurally younger than the men's game despite increased media attention and publicity. To systematically assess performance, this study draws on Dean Oliver's Four Factors, a prominent basketball framework for identifying KPIs. Oliver (2004) identified effective field goal percentage, turnover rate, offensive rebounding percentage, and free throw rate as primary drivers in determining a team's likelihood of winning. These factors are essential for evaluating box score statistics and provide a foundation for the current analysis, aligning the study with established performance metrics in basketball analytics and their prevalence among coaches.

In addition, this study considers other statistical dimensions not captured by the Four Factors or in previous research, including athlete workload and pace of play. Examining how variations in these factors influence game outcomes is essential for data-driven decision-making in modern women's basketball. It also provides important context for understanding differences in analytics adoption between men’s and women’s programs. This difference reflects the structural youth of women’s basketball, which is rooted in Title IX, a law prohibiting sex-based discrimination in educational programs and services. Although Title IX does not explicitly address athletics, it was crucial in expanding athletic opportunities for women, including participation in basketball (Friestedt, 2023). By the 1980s, women accounted for about one-quarter of National Collegiate Athletic Association (NCAA) athletes and participated in the first Division I Women’s Basketball Tournament, approximately 40 years after the first men’s tournament (National Collegiate Athletic Association, 2023).

This relative youth is also evident in the integration of analytics in the women’s game. Its delayed institutional development has meant that analytical systems, resource allocations, and statistical databases have had less time to mature. While structurally younger, the women’s game is not considered any less competitive than the men’s game, evidenced by higher viewership in comparable televised events in recent years (NCAA, 2025). In fact, women’s basketball is often more competitive in the present day, where student-athletes are at the forefront.

The current landscape of collegiate sports is widely defined as the Name, Image, and Likeness (NIL) era, where the monetization of student-athletes’ personal brands has become a central feature (Kunkel, 2021). The heightened visibility and investment in student-athletes marks a crucial moment for the integration of data analytics in women’s basketball. Recent developments underscore the transformative potential of analytics in enhancing performance, informing decision-making, and influencing the strategic evolution of the sport (Brewer et al., 2025).

Coaches are looking to gain a competitive advantage by implementing data-driven approaches to game strategy development, adjusting effectively to real-time challenges, and optimizing player performance (Rauff et al., 2022). The demand for analytics is present, but there has not been a significant call for a systematic implementation of analytics in women's basketball. Analytics remain limited to the scope of the men's game. Overall, there is a need for analytics because players and coaches are eager to know their performance measures, especially with the recent growth of the women's game. These basic measures can be found by examining statistics from a table as simple as a box score.

Box score statistics provide meaningful objectivity to coaches, players, and sports performance staff. How a team chooses to utilize them is the challenge. The National Basketball Association (NBA) is a trailblazer for analytics (Wang et al., 2025). The procedures outlined in Baghal (2012) demonstrate that the analysis of statistics is key to the professional men's basketball game. Box score metrics allow for comprehensive offensive and defensive assessments of individual NBA teams. In other professional leagues, including the Euroleague and Spanish Basketball League, similar analyses of box score statistics have been conducted. Plakias et al. (2024) focused on the comparison of key performance metrics to determine how organizations adapt and win more.

Discriminating between wins and losses is another dimension that box score statistics can provide, which Ibáñez et al. (2008) detailed. How game preparation, scouting, and in-game adjustments play a role in winning are primary factors explained by analytics. Based on the extensive literature and analytical tools developed, there are abundant resources on the men's side of basketball (National Collegiate Athletic Association, 2022). This has led to the continued integration of data in the game, becoming a central aspect of any team's approach to maximizing player performance and increasing the likelihood of winning. Despite the widespread adoption of analytics in performance optimization, the depth of analysis devoted to women's basketball remains comparatively underdeveloped relative to the men's game.

Leicht et al. (2017) provide a framework for examining box score statistics indicative of success in women's basketball during the 2004-2016 Olympic Games. The study references how strategies can be developed with proper assessment of KPIs. Although extensive study at the international level has been undertaken, investment in analytics within professional and collegiate women's basketball remains limited, largely due to gender-based equity disparities and lack of financial investment.

While this study does not seek to address those disparities directly, the results demonstrate the immense potential impact of an analysis of winning-based KPIs in women's college basketball. This analysis informs coaching decision-making across multiple areas, including training design, game strategy, recruiting, and athlete evaluation. By examining the key statistical factors that most strongly influence the most fundamental measurable outcome – winning – this research illustrates the leverage that analytics can provide in advancing the women's game.

Purpose of the Study

The purpose of this study is to analyze the KPIs that drive success in collegiate women's basketball (WBB). In this study, a comprehensive team-level analysis of KPIs and their impact on game outcomes was conducted. Currently, there are no known published studies that have conducted an analysis of this type with direct application to collegiate women's basketball. The extent of analytics remains largely concentrated on the men's side, where data analysts generally operate in closed environments with limited public accessibility and, more importantly, findings are withheld from competitors. This study examines the relationships between team-level offensive and defensive KPIs and game outcomes to determine the statistical thresholds necessary for maximizing the likelihood of winning. This research and further investment in analytics on the women's side of basketball are key to providing insights that will further enhance strategy development and game planning for coaches.

Research Questions

RQ1. What key performance indicators are associated with winning across teams from an NCAA Division I Power 4 WBB conference?

RQ2. What statistical thresholds in key performance indicators must a specific NCAA Division I WBB Power 4 team achieve to maximize the likelihood of winning?

RQ3. Are variations in athlete workload related to pace of play and game outcomes for a specific NCAA Division I WBB Power 4 team?

Significance of the Study

The integration of analytics in basketball coaching provides meaningful solutions to gaining competitive advantage in the sport. The development of game strategy and optimization of player performance ultimately leads to improved results by way of winning. A data-informed decision-making process proves useful in maximizing the potential results. There is always a subjective component to coaching, but integrating data contributes to objectivity in decisions regarding player personnel, scouting, and game strategy development.

The statistical analyses conducted in studies such as those outlined in Plakias et al. (2024) and Ibáñez et al. (2008) have not been extensively applied to women's basketball. Outside of an analysis from Leicht et al. (2017) detailing KPIs of success in the Olympic Games, substantial literature does not exist. The only related research at the women's basketball collegiate level was conducted by students at Sacred Heart University, who developed an R Analytics tool to provide statistical insight into team performance. Juliano and Thakker (2023) created the tool to monitor trends in player and team performance, giving way to data-driven game planning. This study had a similar objective but advances the analysis beyond performance trends by focusing on box score KPIs of a different team and their respective impact on winning.

This study implements a retrospective approach by analyzing historical box score data of teams from a National Collegiate Athletic Association (NCAA) Division I Power 4 WBB Conference from the last four seasons. Box scores from the 2021-22, 2022-23, 2023-24, and 2024-25 seasons were examined to find common themes between statistical measures and identify KPIs. In this study, correlations and a panel binary logit were the primary methods of determining statistical predictors of winning in the sport. KPIs provide marginal benefits by assessing the relative importance of specific indicators of success. These analyses generated predictive analytics as well as a game model for winning, designed for improved decision-making for basketball coaches. The implementation of this tool serves as a starting point for analytical approaches to coaching in collegiate women's basketball.

Delimitations

This study focuses on examining the key performance indicators of teams from an NCAA Division I WBB Power 4 conference, including one team of interest, across the 2021-22, 2022-23, 2023-24, and 2024-25 seasons. The Power 4 conference was selected due to its high visibility, significant media exposure, and substantial revenue generation associated with broadcasting rights and NIL. The team of interest was selected based on data availability across the study period. While the dataset represents a specific competitive environment, the analytical process used in this study provides a replicable framework for evaluating team performance within similar contexts.

CHAPTER 2. REVIEW OF LITERATURE

In relevance to the analysis of KPIs associated with winning in NCAA Division I Women's Basketball (WBB), this literature review consists of four thematic sections, followed by a summary of the findings. The chapter beings with an overview of the literature search process, background information on the sport of basketball, and current state of the women's game. Each section that follows considers research that uses retrospective approaches to analyze statistical performance indicators of basketball success. The first section reviews the methodology related to conducting basketball analytics. This includes an overarching analytical approach, modeling player and team performance, and discussion about various types of methods used for discriminating KPIs and player contribution to team outcome. The second section continues discussion on methodology, specifically an established team-level analysis framework for evaluation. The third section focuses on literature that utilizes binary logistic regression to predict winning in sports. It also mentions effective ways to present basketball data and improve predictive analytics. The fourth section introduces training load metrics and their potential impact on winning, a dimension that remains largely unexplored in basketball analytics literature. The final section is a summary of the literature findings.

Literature Search Process

In the search process for relevant literature, two main bibliographic databases were used. *SPORTDiscus*, which provides a collection of sports and sports medicine research, and *Google Scholar* were used. "Key performance indicators" and "binary logistic regression" were primary root terms of the search. The terms that yielded the most specific results across the respective databases were the combination of "key performance indicators" and "women's basketball." There was one search result for this combination from each database, respectively. In the screening process, literature centered on athletic training and sports science was excluded as this study focuses primarily on statistical box score trends. The review included a total of 23 sources. A full breakdown of results by search term and database can be found in Appendix A.

Basketball Foundations

Basketball Origins

This section outlines the history and rules of basketball, highlighting the sport's origins to the expansion of the women's basketball game. Invented in 1891 by Dr. James Naismith, basketball was originally designed as an indoor sport to stay active during the winter months (Nourayi, 2020). Naismith developed 13 rules to create a fast-paced, exciting game while minimizing violence and injury. Early developments in the sport included the establishment of professional basketball leagues and collegiate basketball programs, including Yale, Minnesota, and Navy. To enforce rules and promote the game, the Intercollegiate Athletic Association formed in 1910, followed by the American Basketball League for professional play in 1925. Throughout the 20th century, basketball's popularity grew rapidly through exposure in the Summer Olympic Games, the formation of the National Basketball Association (NBA) in 1949, and the recognition that the sport welcomes players of varying skills at all levels (Nourayi, 2020).

Basketball Gameplay

Basketball is generally played in either four quarters or two halves, depending on league type. The NBA uses four 12-minute quarters, women's college basketball uses four 10-minute quarters, and men's college basketball plays two 20-minute halves. Two teams each have five players on offense and five on defense simultaneously, with the primary objective being to score points by shooting a ball through a hoop. While gameplay varies across professional and collegiate levels, the sport has evolved into a fast-paced, strategic game with three main positions. Guards handle the ball and facilitate offense, forwards balance scoring and defense, and centers focus on rebounding and controlling the interior court. These positions, combined with tradition, athleticism, and strategy, form the foundational elements of basketball.

History of Women's Basketball

Women's basketball has developed its own history based on the broader foundations of the sport. While the NCAA was founded in 1906, the first official women's basketball tournament did not occur until 1982 (National Collegiate Athletic Association, 2023). Decades of advocacy for women's rights in the United States corresponded with the call for institutional support of women's athletics, culminating with the passage of Title IX (Friestedt, 2023). The law was crucial in the expansion of athletic opportunities for women and the rise of basketball popularity from its early origins to recent years. Trailblazing athletes have been critical in elevating women's college basketball, establishing it as the widely recognized women's team sport. In recent years, players such as Caitlin Clark and A'ja Wilson have been instrumental in significantly increasing the game's popularity (Grundy & Shackleford, 2025).

Equity Challenges

The transformative power of the sport was exemplified by record-breaking viewership during the NCAA women's basketball championships (NCAA, 2025). Despite this reality, investment in analytics within professional and collegiate women's basketball remains limited, largely due to gender-based equity disparities and lack of financial investment. Division I athletic departments continue to allocate substantially more resources to men's versus women's programs, spending roughly twice as much each year (National Collegiate Athletic Association, 2022). Women also remain underrepresented in leadership roles, accounting for about 25 percent of all head coaches and athletic directors in the NCAA (2022).

Salary disparities also reflect this imbalance between men and women. *USA Today* reported in 2024 that women's basketball coaches make about 27 cents for every 1 dollar compared to men's coaches, about a four times difference in average pay. Despite the explosion in media visibility and growing popularity of the women's game, these figures demonstrate that gender equity remains an ongoing challenge.

The differences across gender lines apply to analytics as well. Information on analytics is widespread, but sources specifically focused on women's basketball have only recently become available, such as CBB Analytics, Her Hoops Stats, and Synergy Sports. Additionally, there is not yet an established presence of analytics-specific positions within women's basketball. This lack of dedicated analytical resources highlights the broader disparities in athlete health and support services, roster sizes, and match congestion between the men's and women's games. At this crossroads for women's basketball, exploring the strategic potential of analytics presents an opportunity to enhance performance, inform strategic decision-making, and continue to grow the game.

Methodology of Basketball Analytics

This section focuses on the analytical approaches to evaluating basketball team performance. The identification of KPIs of success in sports has become increasingly essential to developing game strategy and optimizing performance in recent years. An overarching approach to quantitative analysis in sport is the transition from descriptive to prescriptive analytics, described in detail in Sarlis and Tjortjis (2020). Retrospectively examining data is straightforward due to accessibility, but making predictions and influencing decision-making is a revolutionary component of analytics. Sarlis and Tjortjis (2020) explain that while predictive and prescriptive analytics, or data-driven methods that inform decision-making, requires higher skill level, a greater level of impact results. An increased depth of understanding is crucial to developing critical reasoning for not only why results occurred but how they impact decision-making moving forward.

Identification of KPIs

Another layer of sports analytics is the identification of KPIs. Hughes and Bartlett (2002) state that in net games, there exist biomechanical, technical, and tactical indicators of successful outcomes. Biomechanical factors include the movement patterns of physical body structures in performance. In addition, technical factors include the execution of certain skills, and tactical factors refer to strategies in sport. Technical and tactical factors are especially important in determining KPIs of success in basketball. How teams choose to use pace, space, and fitness are indicative of game strategy and target the strengths and weaknesses of players (Hughes & Bartlett, 2002). Specific to basketball, shot selection, shot execution, possession length, dribbles, and the kinematics of shooting are examples of success indicators in these categories.

Analyzing the technical and tactical indicators of success involves progression from descriptive to predictive analytics. At this greater skill level, it also necessitates the use of data mining and machine learning algorithms. Sarlis and Tjortjis (2020) reference the importance of these algorithms in discovering patterns and key indicators within large amounts of data. The researchers point to the algorithms that can be used in sports, including decision trees, association rule models, Bayesian models, and linear and logistic regression models. These techniques establish a common methodology in literature about sports analytics.

Established Methodology

Two examples about the methodology in assessing the impact of KPIs specific to basketball include case studies about the National Basketball Association (NBA) and Women's National Basketball Association (WNBA). Unique to these studies is the use of multiple linear regression, quantile regression, and multivariate analysis. Zhou et al. (2024) evaluated regular season and play-in playoff games from the 2020-22 NBA seasons. The researchers evaluated the influence of two-point field goal and three-point field goal percentage, rebounds, turnovers, steals, and game pace on game outcome. A main result from the research conducted was that quantile regression analysis is more sensitive than multiple linear regression analysis in evaluating KPIs (Zhou et al., 2024).

Similar to the professional basketball study conducted by Zhou et al. (2024), Gómez et al. (2009) determined the extent to which the same game-related statistics discriminate between players who are considered starters versus non-starters. A multivariate analysis was performed, and a discriminant function for starting status was created in this study. The most powerful statistics that were found in Gómez et al. (2009) were two-point field goals, free-throws, and assists in discriminating between starters and non-starters.

While the methods used by the researchers in the NBA and WNBA case studies varied, they are an exemplification of an established way to analyze KPIs in basketball: team-level analyses. Both studies started with basic box score statistics, including two-point field goals and rebounds, and utilized machine learning or regression analyses to determine model sensitivity and discriminate factors of success. This framework for conducting performance analyses in basketball is discussed in-depth in the following section.

Team-Level Analysis Framework

This section discusses the identification of KPIs in basketball and an idealized framework for analyzing the impact of these variables on game outcome. In the international game, three KPIs are crucial for match success: field goal percentage (two- or three-point), defensive rebounds, and assists (Leicht et al., 2017). In diagnosing basic box score summary statistics, these three KPIs serve as the starting point. They also serve as the source of KPIs for team-level analyses, which are the most frequently used method of evaluating the impact of KPIs on outcome. The most impactful KPIs can vary between professional versus collegiate leagues, conference play versus tournament formats, and men's versus women's basketball. The varying impact of KPIs is due to differing styles of play, physical intensity evolving based on the time of season, roster availability, and changes in tactical strategies, among other factors. Table 1 shows a foundational list of KPIs and their impact on winning.

Table 1

Key Performance Indicators and Associated Expected Relationships to Likelihood of Winning

Key Performance Indicator (KPI)	Relationship to Likelihood of Winning
Field Goal Percentage (FG)	Improves
Defensive Rebounds (DRB)	Improves
Assists (AST)	Improves
Turnovers (TO)	Worsens
Pace of Play (PACE)	Improves or Worsens (depends on play style)
Points (PTS)	Improves

Note. The expected relationships between individual KPIs and winning are found in this table. "Improves" indicates that an increase in a KPI enhances the likelihood of winning, and "Worsens" indicates a decreasing likelihood of winning. Pace of Play (PACE) is an anomaly as it differs between teams, with some better suited for higher pace and others lower pace of play. PACE is an example of several KPIs that vary across teams.

Overview of Olympic WBB Research

Several studies follow a similar retrospective approach in diagnosing basketball KPIs at the team level. Research starts with descriptive analytics, examining variables in a basic team box score. Then, regression or multivariate techniques of analysis are used to determine the weight, or influence, of these box score variables. Finally, the most impactful KPIs are identified and used as evidence for the development of game strategy. The study by Leicht et al. (2017) is a prime example of how to evaluate KPIs that lead to the greatest probability of winning at the Olympic level. Leicht et al. (2017) use women's basketball matches during the Olympic Games from 2004-2016. The researchers of the study used a linear technique of binary logistic regression and a non-linear technique of a classification decision tree to determine winning probabilities. Using the classification tree, a unique combination of field goal percentage, defensive rebounds, steals, and turnovers yielded the greatest probability of winning at 91.1 percent (Leicht et al., 2017). The authors believed that the discovery of these KPIs as most important focuses team preparation related to shooting proficiency and defensive actions. In effect, the research suggested that the team-level diagnosis of these KPIs contributed to the development of game strategy in elite basketball.

An obvious limitation to Leicht et al. (2017) is that the results are not generalizable to other basketball leagues, which is a threat to the external validity of the study. Leicht et al. (2017) only considers the Olympic Games, which are in a confined environment with a large disparity between the elite and subpar national teams represented. Generalizing this to the WNBA, for example, is not feasible. WNBA seasons consist of regular season and playoff games, with the stakes different for each game. Additionally, one consistent feature of WNBA games is due to the high level of competition, which is not necessarily present in the Olympic

WBB games. International teams vary in their playing styles and often lack the overall talent of United States teams. In particular, the United States has won eight consecutive gold medals, with most of their wins by greater than 10 points (Reuters, 2024). Another noteworthy aspect not included in Leicht et al. (2017) is the absence of accounting for regional and international gameplay locations as all Olympic Games are played on a neutral site.

Other Retrospective Analyses

Additional studies with similar methodology exist, including Akers et al. (1991) and Baghal (2012). Akers et al. (1991) consisted of an empirical study into the success factors of NCAA Division I Men's Basketball teams, finding that two-point field goal percentage is most indicative of success. Similarly, the study by Baghal (2012) found a method of predicting winning percentage in the NBA by using offensive and defensive quality factors. The ratings were found through structural equation modeling (SEM) and a regression analysis of effective field goal percentage, free throw rate, turnovers per possession, and offensive rebounding percentage. These variables were derived from Dean Oliver's Four Factors of basketball success, which is discussed further in the next section.

The established methodology described in Akers et al. (1991), Baghal (2012), and Leicht et al. (2017) is a foundational approach to performing basketball statistical analyses. When combined with more robust statistical methods, these approaches to KPIs can offer practical applications to coaches. Binary logistic regression, maximum likelihood estimation, and decision tree modeling provide enhanced statistical power. The methods included in literature from Gifford and Bayrak (2023) and Tomanek et al. (2025) provide a meaningful framework to generate predictive analytics. The following section will examine these statistical methods and expand on those presented in Leicht et al. (2017).

Binary Logistic Regression in Sport

This section describes research that has utilized binary logistic regressions to identify KPIs of success in related sports. In literature, studies with binary logistic regressions have typically included one binary dependent variable and a set of predictors in each model. The target variable in these studies was the win-loss game outcome. Leicht et al. (2017), Gifford and Bayrak (2023), and Tomanek et al. (2025) generated predictive analytics using binary logistic regression in basketball and football to identify significant predictors and forecast outcomes.

Olympic WBB Research

The study by Leicht et al. (2017) on the Olympic Games from 2004-2016 used binary logistic regression as a linear statistical technique to identify KPIs in Olympic WBB matches. Match outcome was the binary target variable, coded as a win or loss in a given match. Model parsimony was conducted through the delta Akaike Information Criterion (AIC) and Akaike weights to determine the simplest and most effective model for the binary logistic regression (Leicht et al., 2017). At a classification accuracy of 85.6 percent, the model included defensive rebounds, field-goal percentage, offensive rebounds, fouls, steals, and turnovers as the set of indicators. These variables accounted for 88.5 percent of the wins and 89.1 percent of the losses.

Leicht et al. (2017) also use a conditional inference classification tree (CIT) as a non-linear technique. This expanded on the binary logistic regression by finding a unique combination of factors that provided the highest likelihood of winning. The combination of at least 62.2 percent field-goal percentage, 30.8 defensive rebounds, 9.3 steals, and less than 36.6 turnovers in each Olympic WBB game yielded a 91.1 percent likelihood of winning (Leicht et al., 2017). The establishment of team statistical thresholds for winning and losing are meaningful benchmarks for coaches to utilize. Understanding the benchmarks for certain statistics in each game drives scouting and game planning procedures. This study shows how combining a binary logistic regression to predict wins versus losses with a decision tree model to identify game performance standards provides coaches with an effective practical framework for preparation and strategy.

Logit in NFL Statistics

Gifford and Bayrak (2023) employed a logistic regression model to analyze National Football League (NFL) team statistics from 2002-2018 to forecast game outcomes. The maximum likelihood estimation method drove the statistical analysis, with significant predictors identified using β coefficients, p-values, and odds ratios. Offensive and defensive turnovers were identified as the most important factors as they had the largest negative and positive effects on game outcome with β coefficients of -0.9686 and 0.9124, respectively. Additionally, defensive turnovers had the largest point estimate, meaning that a one-unit change in turnovers contributed the most in determining a team's win or loss in a given game (Gifford & Bayrak, 2023).

The statistical power of turnovers and their associated impact on NFL game outcomes was demonstrated in the coefficient and point estimate tables. This shows that a single turnover can be the difference between a win and loss for a given NFL team. To determine the predictive accuracy of the model, the authors applied the logistic regression model to the 2018 NFL regular season, comparing the model win-loss output to the actual standings. Gifford and Bayrak (2023) found a misclassification rate of 16.9 percent, meaning their model successfully predicted wins 83.1 percent of the time in 2018 regular season games.

Men's Olympic Basketball Tournaments

Similar methodology to Gifford and Bayrak (2023) was employed in Tomanek et al. (2025), an analysis of KPIs across 62 games in the 2024 Men's Olympic Tournament and

Qualifying Tournaments. Three statistical indicators were tracked across the games: 3-point percentage (3PT%), rebound percentage (REB%), and turnover percentage (TOV%). The authors cited the rise of 3-point shooting in modern basketball, prior research identifying defensive rebounds as a key differentiator of wins from losses, and the value of each possession in justifying their focus on these three variables. A binary logistic regression was used with the maximum likelihood method to identify the significance of these factors on game outcome.

From the model results, all three statistics were considered significant predictors of winning in the Olympic Qualifying Tournaments. The predictors accounted for a large variation in game outcome at an R-square of 0.552. For every one unit increase in 3PT%, the odds of winning increased by 13 percent. For rebounds and turnovers, this corresponded with a 29 percent increase and 24 percent decrease, respectively. These results provided statistical support for coaches to prioritize 3-point shooting efficiency, rebounding, and minimizing turnovers to increase the probability of winning basketball games.

Four Factors Model

Leicht et al. (2017) and Tomanek et al. (2025) demonstrate that success in basketball is driven by improved shooting efficiency, strong rebounding, and reduced turnovers. These represent three of Oliver's Four Factors (2004). Oliver identified four KPIs that explain how basketball teams win games: effective field goal percentage (eFG), turnover percentage (TOV%), offensive rebounding percentage (OREB%), and free throw rate (FTR). Effective field goal percentage (eFG) is an adjusted field goal percentage that reflects the added value of three-point shots. Because three-pointers are worth one more point than two-pointers, eFG weighs three-pointers by an additional 50 percent, providing an accurate representation of a player's scoring efficiency (Oliver, 2004).

In *Basketball on Paper* (2004), Oliver introduced a set of KPIs that were coined as the Four Factors, each weighed by their relative impact on winning: shooting efficiency (40 percent), turnovers (25 percent), rebounding (20 percent), and free throws (15 percent). Oliver argued that these Four Factors provide a comprehensive framework for evaluating how teams manage possessions, ultimately reflecting their ability to win games. The methodologies applied in Leicht et al. (2017), Tomanek et al. (2025), and Gifford and Bayrak (2023) demonstrate effective approaches for identifying KPIs linked to winning. By adopting similar analytical frameworks, the Four Factors can be operationalized within statistical models to support and validate the underlying theoretical concept. Furthermore, the integration of binary logistic regression, independent samples t-tests, and decision tree modeling presents a threefold analytical approach to identifying the greatest probability of winning. Figure 1 presents the conceptual framework that guided this study, outlining how these analytical methods were used to address the research questions. Within this framework, training load metrics serve as an exploratory component for understanding team performance.

Training Load Metrics

This study explores training load monitoring in sports, which is emerging as a critical component of athlete performance and injury prevention. Training load, also referred to as athlete workload, is the physiological and mechanical stress placed on an athlete during practices and games (Gabbett, 2016). It is often measured through internal metrics, such as heart rate, and external metrics, including movement patterns and duration. Catapult is a primary tool for measuring external workload of an athlete and serves as the primary tool for data collection in this study.

Recent developments in sports science underscore the importance of load monitoring in elite sports, particularly in football, soccer, and basketball. Despite the prevalence of training load as a measure of athlete performance, its direct relationship to game outcomes remains largely unexplored. Typical sports science research focuses on injury risk and recovery but does not connect training load to KPIs, such as PACE, FG, or TO (Gabbett, 2016). Additionally, sports science data is proprietary and limited to internal use among teams, which restricts its availability for public research.

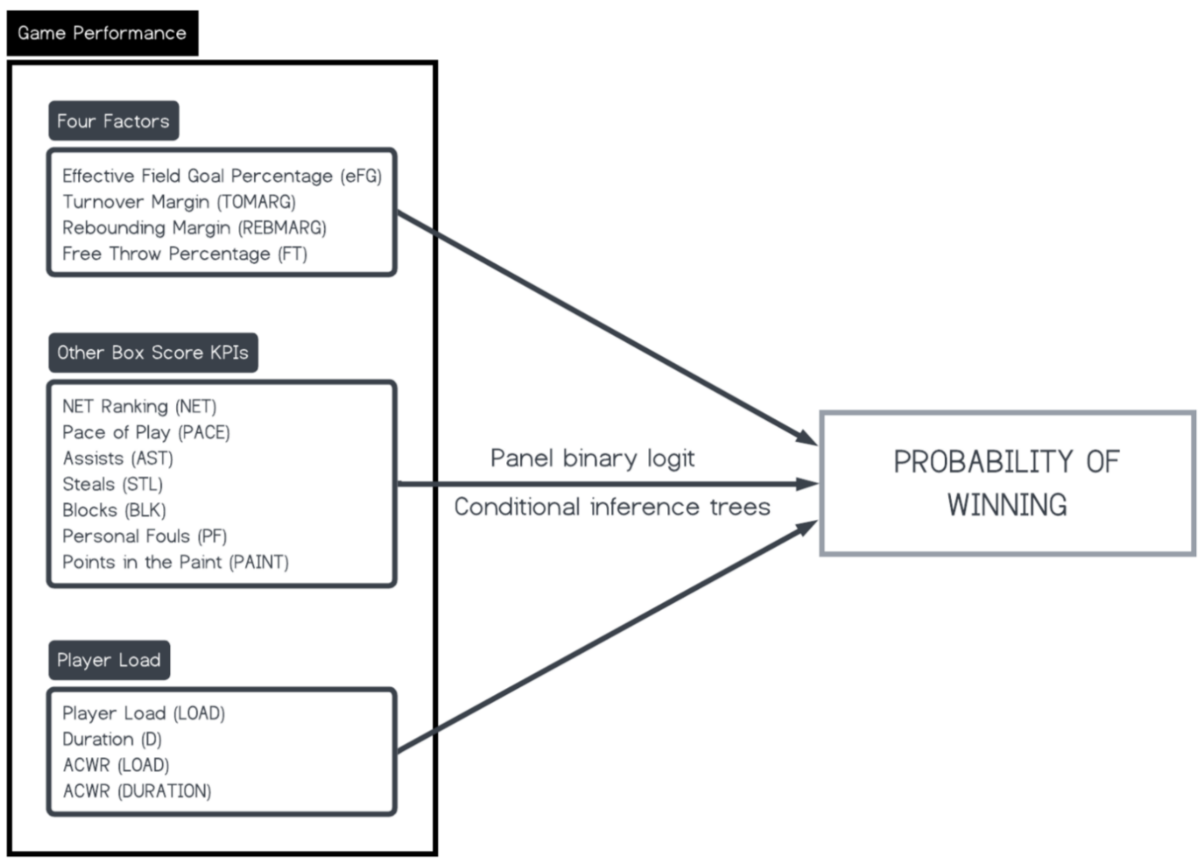
This lack of accessible data helps explain the limited integration of training load into performance outcome modeling and justifies the use of the "team of interest" approach employed in this study. This approach combines box score statistics with athlete workload metrics and represents a novel extension of existing KPI frameworks. Therefore, examining the impact of training load within a KPI analysis has the potential to provide a more comprehensive understanding of performance in WBB.

Summary of Findings

Sports analytics literature references the growing importance of moving across the continuum from descriptive to prescriptive analytics. This idea encourages the development of a standard methodology for analyzing KPIs in basketball. An established framework that many studies use starts with a descriptive analysis of basic KPIs at the team level. Then, the KPIs most strongly associated with winning are identified by incorporating machine learning and regression analyses. There are several considerations from literature that serve as useful applications to analyze KPIs in NCAA Division I WBB. In sound analytical approaches, the evaluation of KPIs at the team level accounts for differences in game type (conference versus non-conference), situational factors (home versus away), and opponent strength. This study identifies KPIs and analyzes their relationship with winning, contributing to the development of improved strategies through predictive modeling. This analysis provided meaningful insights from a panel logit and established statistical thresholds required to win. Overall, these results serve as the foundation for developing an objective game model that maximizes winning for NCAA Division I WBB teams in a technical and tactical manner.

Figure 1

Concept Map of KPIs and Winning



Note. The concept map illustrates game performance metrics modeled by KPIs and their relationship with the probability of winning. KPIs are categorized into the Four Factors unique to this study, additional KPIs, and player load metrics. These KPIs are defined in Table 3. Panel binary logit and conditional inference trees (CITs) were used in this study to estimate the probability of winning based on KPIs.

CHAPTER 3. DESIGN AND METHODOLOGY

Chapter 3 discusses the design of the study and methodology employed to analyze the associated research questions. The chapter begins with a description of the sampling techniques used as well as the measurement protocols. The section then transitions to discussion of the research design and data collection procedures. The chapter concludes with a description of the procedures for data management and methods for data analysis.

This study's research questions focused on identifying key performance indicators in NCAA Division I WBB that lead to the highest likelihood of winning. To uncover the relationship between KPIs and winning in WBB, correlational and binary logistic regression analyses were conducted. Research from Leicht et al. (2017), Gifford and Bayrak (2023), Tomanek et al. (2025), and Oliver (2004), drove the process of identifying the most impactful KPIs on winning and employing specific methodology to WBB teams. Using historical data from the past four seasons, this study diagnosed winning for the team of interest as well as all teams from a Power 4 conference. The results of this research can be applied and replicated for coaches at other NCAA Division I WBB programs.

Sample

There are currently 351 NCAA member schools in WBB and nearly 17,000 players. From this population of interest, a convenience sample of all 16 WBB teams from the current Power 4 conference from the 2021-22, 2022-23, 2023-24, and 2024-25 seasons was selected. As the research design suggests, this was a study of publicly observable historical basketball data, so recruitment of athlete participants was not necessary. The data was split into two for modeling purposes. One model focused on all selected Power 4 conference teams, which includes the team of interest, and the other focused on only the team of interest. Across the four seasons, there were a total of 2,128 games played by the Power 4 conference teams and 135 games played by the team of interest. Table 2 shows the player and game breakdown by season.

Table 2

Women's Basketball Game Breakdown by Season, the Power 4 Conference, and Team of Interest

Season	Power 4 Conference # of Games	Team of Interest # of Games
Overall	2,128	135
2021-22	517	34
2022-23	536	33
2023-24	535	33
2024-25	540	35

Note. The table depicts the number of games played across the 2021-25 seasons and an aggregate total for the Power 4 conference teams and the team of interest.

A study by Leicht et al. (2017) determined KPIs of Olympic female basketball success over the course of 156 Olympic Games from 2004-2015. This study was similar in its sampling timeframe and technique as data collection occurred across years of play.

Measurement Protocols

This section describes the measurement tools and procedures of this study. The data measured consists of KPIs, which are found by scraping box score summary statistics from sports reference pages. In this study, The Basketball (college) page from Sports Reference was used as it provides accurate, historical box score data and the KPIs of interest (2026). The data scraped included team-level box score statistics, such as pace of play (PACE), field goal percentage (FG), and rebounds (REB), found in Table 3. KPIs are validated because they quantify marginal effects on game outcomes, are readily accessible and measurable, and allow for performance comparison across games and teams. The research design to measure these KPIs are discussed in the following section.

Research Design

The focus of this section is on the correlational design of this research. By examining the statistical relationships between independent and dependent variables, without manipulation or control, associations between these variables were established. In this study, the independent variables were the KPIs, using the methodology described later in this chapter. The dependent variable was game outcome. This result was a binary variable, marked as a win or a loss. Establishing statistical relationships between KPIs and the likelihood of winning answered the research questions. The statistics of individual KPIs were examined to discover the most impactful KPIs on winning.

Confounding Variable Treatment

A methodological concern is the study design was the presence of confounding variables, or unobserved factors that could influence predictor variables and outcomes. This study limited potential sources of bias due to historical factors, team maturation, and generalizability through multiple strategies.

History refers to events that may have occurred over the course of the basketball season that do not appear as a measurable performance statistic in a box score. For example, the team of interest may have gradually improved their athletic performance due to psychological factors, such as team chemistry or dynamics. Injuries and coaching staff changes are other factors that may have caused changes in athletic performance and affected game outcomes. The ever-changing landscape of college athletics, marked by the transfer portal and NIL, was also considered. These factors were accounted for in the model by using team-year fixed effects. This involved creating a dummy variable for each team in each season, which captured psychological factors, roster composition differences, and other unobserved factors. As team characteristics evolve across seasons, controlling for these confounding variables was crucial to maintaining the validity of the study.

Maturation was another confounding variable, particularly in relation to physical growth and skill development over time. Sports science data from the strength and conditioning program of the team of interest was incorporated to address this concern. This data was explored descriptively using the team of interest's Player Load (LOAD), Duration (D), Acute to Chronic Workload Ratio of Player Load (ACWR (LOAD)), and Acute to Chronic Workload Ratio of Duration (ACWR (D)) metrics. Player load is a measure of total physical workload for an athlete for movement in all planes, and duration is the activity time for an athlete, both derived from Catapult. Acute to Chronic Workload Ratio (ACWR) compares acute workload (1 week) and chronic workload (4 weeks) to estimate injury risk and fatigue for athletes (Towner et al., 2023). In this study, the exponentially weighted moving average (EWMA) of the prior 7 days over the prior 4 weeks was used to calculate ACWR. While the LOAD-related variables were not the focus of this study, the EWMA ACWR offers a more sensitive measure of injury risk, can detect spikes in athlete workload, and gives more weight to recent days before games (Murray et al., 2017). Data collection procedures for the strength and conditioning metrics are described in the next section.

These metrics offered insight into the physical evolvement of athletes and how performance loads changed with intensity and volume. Physical maturation and varying performance loads are a few potential factors of changes in player and team statistics throughout the season. With additional research in this area of basketball, the knowledge of the LOAD and

ACWR factors could enable a more comprehensive analysis of performance outcomes and control maturation effects further.

As research was focused on a single WBB conference, generalizability was another confounding layer. NCAA Division I WBB programs vary in style of play, personnel, training regimen, and team culture. Because this study focused on a Power 4 conference, where NIL opportunities, resource availability, and media exposure are comparatively higher, the findings may not generalize to programs with fewer resources or lower visibility. Replicating this study across institutions is therefore critical for developing team-specific game strategies and competitive advantages. Understanding that KPIs may change between teams is vital when replicating the procedures outlined in this study. For example, a team may average the greatest number of possessions in the nation and tactically focus on scoring quickly in transition. KPIs responsible for winning may include PACE and FG. In contrast, a different team may slow their pace and run primarily half-court offense. The team that is playing at a slower pace may have KPIs that differ immensely from the other team.

The purpose of this example is to show that, when generalizing the results or replicating this study, a team-specific approach must be employed for individual WBB programs. Considering these differences, the results of this study may help identify the KPIs most influential for teams at varying PACE levels. This study explored stratification of teams based on pace of play to address this concept between PACE groups. The statistical KPIs that were measured in this study are discussed in detail in the next section.

Data Collection Procedures

This section discusses the procedures related to the collection of statistical basketball data. Team statistics for the 2021-22 through 2024-25 seasons were collected between October

2024 and April 2025. Quantitative, historical performance data was the focus of this study. This data included statistical KPIs and game outcomes counted as wins and losses, with multiple data points collected each game. Team-level statistics included box score summaries, comprised of the KPIs shown in Tables 3 and 4.

The year, location (home, away, or neutral site), game type (conference, non-conference, or tournament), opponent strength (NET ranking), and result (win or loss) were also included in data collection. The NCAA Evaluation Tool (NET) was used to assess overall opponent strength. The end-of-year NET was used in this study due to data availability. The NET ranking is a combination of the Team Value Index (TVI) and an adjusted net efficiency rating (Wittry, 2025). In essence, the NET measures a team's net efficiency and adjusts based on location and opponent strength. It is a key metric that the NCAA Tournament Selection Committee uses in evaluating and seeding teams in the NCAA Tournament (Wittry, 2025).

Additional data included the performance variables LOAD, D, ACWR (LOAD), and ACWR (D), unique to the team of interest. These metrics were limited to the team of interest due to data availability and athlete confidentiality standards. Load and duration variables were collected from the team of interest's strength and conditioning database, which included Catapult observations from 2021-25. The Catapult system utilizes wearable GPS technology to monitor player movement and intensity, providing an estimate of external workload. Each device contains a microsensor unit equipped with triaxial accelerometers, gyroscopes, and magnetometers, capturing movement across multiple planes to quantify dynamic athlete movement (Catapult, 2018).

Player load (LOAD) and duration (D) are derived from Catapult data, with inertial sensor data sampled at a frequency of approximately 100 Hz (Catapult, 2018). This data varied in availability across the four seasons as the team of interest increasingly used Catapult as the timeframe of the study progressed. The caption in Table 12 includes a breakdown of the total games the data included. Permission from the team of interest's strength and conditioning staff was granted to use the dataset.

Table 3

Predictor Variables for Team-level Statistics with respective units

Measure	Variable	Operationalization
Team	Team-year fixed effects (Team_Year)	Dummy variables for each team-season control for unobserved heterogeneity across teams and seasons
	NET Ranking (NET)	NCAA Evaluation Tool (NET) that measures team's efficiency and overall strength
	Opponent NET Ranking (OPP_NET)	NET Ranking for opponent
	Pace of Play (PACE)	Estimated number of total possessions in game (0.5 * [team possessions + opponent possessions])
	Total Rebounds (TRB)	Total rebounds secured by team (offensive + defensive)
	Rebounding Margin (REBMARG)	Team total rebounds – opponent total rebounds
	Turnover Margin (TOMARG)	Opponent turnovers – team turnovers
	Personal Fouls (PF)	Total number of fouls committed by team

Note. KPIs for the team-level analysis in the study for team-level statistics.

Table 4

Predictor Variables for Offense, Defense, and Training Load with respective units

Measure	Variable	Operationalization
Offense	Points (PTS)	Total points scored by team
	Field Goal Percentage (FG)	Field goals made divided by field goals attempted (FGM / FGA)
	Two-Point Field Goal Percentage (2PT)	Two-point field goals made divided by two-point attempts (2PM / 2PA)
	Three-Point Field Goal Percentage (3PT)	Three-point field goals made divided by three-point attempts (3PM / 3PA)
	Effective Field Goal Percentage (eFG)	(FGM + 0.5 * 3PM) / FGA
	Free Throw Percentage (FT)	Free throws made divided by free throws attempted (FTM / FTA)
	Offensive Rebounds (ORB)	Total offensive rebounds by team
	Assists (AST)	Total assists (on FGM) by team
	Turnovers (TO)	Total turnovers (lost ball control) by team
	Points in the Paint (PAINT)	Total points scored by team in painted area of court
Defense	Defensive Rebounds (DRB)	Total defensive rebounds by team
	Blocks (BLK)	Total blocked shots by team
	Steals (STL)	Total steals (taken opponent possessions) by team
	Opponent Offensive Variables	Same offensive metrics calculated for opposing team
Training Load	Player Load (LOAD)	Composite measure of external athlete workload derived by Catapult (*a.u.*)
	Duration (D)	Total participation time per player (*sec*)
	Acute to Chronic Workload Ratio of LOAD	Ratio of exponentially weighted moving average (EWMA) of LOAD of prior 7 days over prior 4 weeks (*a.u.*)
	Acute to Chronic Workload Ratio of D	Ratio of EWMA of D of prior 7 days over prior 4 weeks (*a.u.*)

Note. KPIs for the team-level analysis in the study, in offensive, defensive, and training load categories. The training load variables were specific to the team of interest model only.

The Catapult data was presented at an individual player level, and it was anonymized and de-identified to protect individual privacy. The data was averaged by date, and player entries were removed when the player did not average at least 10 minutes per game, or a quarter, in that season. Then, team averages were calculated, and the EWMA ACWR was calculated from the *Science for Sport* ACWR calculator (2026). The ACWR values calculated for player load and duration up to the day before the game were entered into the dataset. The final section of this chapter focuses on data analysis procedures.

Data Management and Analysis

Data Cleaning

This section focuses on the data management procedures and statistical tests that were conducted in this analysis. Microsoft Excel served as the primary structured database for the large datasets. All files were converted to the comma-separated values type for ease of exchange and compatibility purposes. Data from Sports Reference was entered into these files. Two key aspects of data entry included the creation of templates and data cleaning. A template that includes year, location, game type, opponent strength, and result allowed for consistency across datasets that differed in collected statistics. To validate data accuracy, data cleaning was necessary. Three games were deleted because the games were recorded but cancelled due to health and safety protocols or teams electing to not participate in games due to limited roster numbers. LOAD and ACWR values were examined for outliers or missing data. In addition, approximately 30 random games were checked for inconsistencies and mistakes in data entry. These were cross-checked with box scores from other sports reference pages, contributing to a well-structured dataset.

Statistical Analyses

Descriptive, diagnostic, and predictive analytics and their associated statistical tests were incorporated in this study. This study followed the procedures outlined in Leicht et al. (2017), Gifford and Bayrak (2023), and Tomanek et al. (2025). KPIs were the independent variables, and the binary dependent variable was game outcome, coded as wins and losses. All statistical analyses were conducted using IBM SPSS Statistics Version 31 and R Version 4.5.3. Descriptive statistics included the mean and standard deviation for each KPI. For the correlational aspect of the study, Pearson's *r* measured correlations between KPIs and winning. Independent sample t-tests determined which KPIs had the greatest statistical difference in wins versus losses.

Collinearity

Collinearity is a common issue that arises when performing statistical analyses on box score data. Collinearity occurs when two or more KPIs are highly correlated. For example, field goal percentage is often correlated with field goals made. To detect collinearity, the variance inflation factor (VIF) was calculated, with values above 5 generally considered indicative of moderate to severe collinearity (O'Brien, 2007). Collinearity between KPIs can produce unreliable regression coefficients, increase the risk of Type II error, and limit the predictive capabilities of models (Yoo et al., 2014). To account for this issue, specific KPIs were aggregated into comprehensive metrics or removed in severe cases of collinearity. Thus, field goals made and field goals attempted were excluded, and field goal percentage was retained, thereby reducing multicollinearity issues in the model.

The remaining KPIs were examined to minimize collinearity. The correlation heat map shown in Figure 2 provides further explanation that guided the reduction of the full performance model, shown in Equation (1). Specifically, FG and eFG exhibited nearly perfect correlation (r =

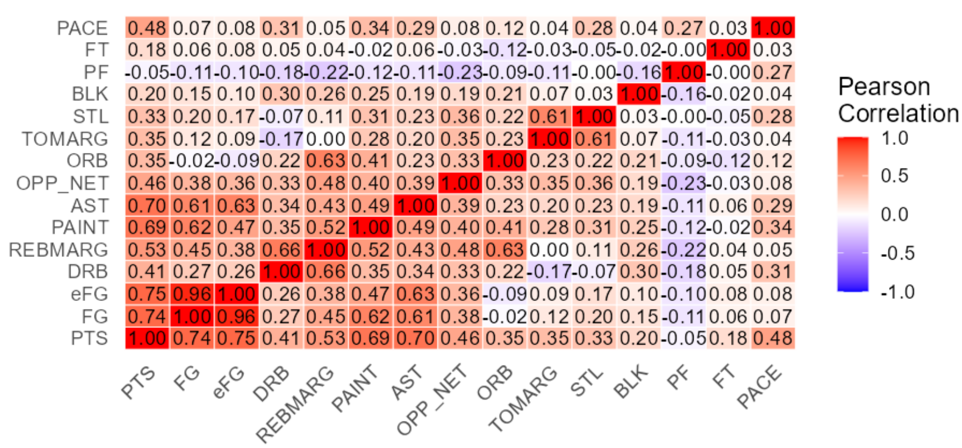
0.96), and DRB was highly correlated with REBMARG (r = 0.66). Consequently, FG and DRB were removed from the model to reduce collinearity and focus on efficiency-based metrics (Oliver, 2004).

Panel Logit

A panel binary logit was employed to examine the relationships between KPIs and game outcome. A Hausman test was conducted to determine whether team-year fixed effects were the appropriate specification for the model. Given that teams were observed repeatedly in the dataset, team-year fixed effects were included to account for season-invariant unobserved heterogeneity, including roster composition and coaching effects. The season factor was tied to team as year-to-year rosters typically change significantly throughout this window, especially since the introduction of transfer portal flexibilities. This resulted in the creation of a Team_Year variable to account for fixed effects.

Figure 2

Correlation Heat Map of KPIs



Note. Heat map showing Pearson correlations between KPIs for all Power 4 conference teams. Red (blue) shades represent positive (negative) correlations, with increasing magnitudes in darker shades.

The logit generated regression coefficients, p-values, and odd ratios to determine the impact of KPIs on outcome. Equation (1) represents the panel logit equation.

$\text{logit}(P(Y_{it} = 1) = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + . . . + \alpha_i$ (1),

where

$Y_{it} = 1$ if team i wins game t, 0 otherwise;

i = Team;

t = Season;

X_{kit} = Predictor k for team i for game t;

β_k = Estimated coefficient for predictor k;

α_i = Team_Year fixed effect.

The coefficients provided an estimate of the variables with the largest effect on outcome, and the p-value indicated the significance of those effects. Furthermore, the odds ratios were calculated by exponentiating the coefficient estimates. For a given KPI, an odds ratio greater than one indicates that the likelihood of a win increases (Tomanek et al., 2025). For example, an odds ratio of 1.5 for a given KPI indicates that the odds of a win occurring increase by 50 percent for every one-unit increase in the KPI. Predictors with similar effect magnitudes were grouped into a set of predictors. The unique set of predictors that accounted for the greatest number of wins, or losses, were considered for practical applications for basketball coaches.

CIT Method

Expanding on the results from the panel logit, the CIT method used in Leicht et al. (2017) was applied. In studies such as Leicht et al. (2017) that involve binary logistic regression, differences between metrics are typically identified, but these studies do not establish statistical thresholds. Combining the methods of a panel logit with automated modeling procedures, such as machine learning in CITs, addressed this research gap. The CITs established statistical thresholds for individual KPIs that best model winning. A unique combination of factors in a game – 82 points, 28 defensive rebounds, and a -1.7-turnover margin – represents the average values for the team of interest and is hypothesized to correspond to the highest probability of winning (H2). Team-year characteristics and opponent strength may also influence performance outcomes, highlighting the importance of accounting for both factors in the model.

Analysis Plan

The analysis plan for this study is presented in Table 5, based on the three research questions. The table details the key variables, hypotheses, and the methodology employed for each analysis.

Based on this plan, a foundational game model was developed, and critical statistical thresholds for coaching strategy decision-making were established to determine the KPIs that maximize the likelihood of winning in WBB. This study provided an objective, data-driven model of success to support WBB coaching staff in their pursuit of achieving competitive excellence in the NCAA Division I landscape.

Table 5

Data Analysis Plan

Research Question	Variables	Hypotheses	Analyses
RQ1: What key performance indicators are associated with winning across teams from an NCAA Division I Power 4 WBB conference?	Dependent variables: Result (W, L) Independent variables: Team-level KPIs; PACE	*H1:* It was hypothesized that for teams with high and moderate levels of PACE, PTS, TRB, and TO were the key performance indicators associated with winning. For teams with low levels of PACE, PTS, TRB, opponent FG and opponent 3PT were the key performance indicators of winning.	Pearson correlation Independent samples t-test Panel binary logit
RQ2: What statistical thresholds in key performance indicators must a specific NCAA Division I WBB Power 4 team achieve to maximize the likelihood of winning?	DV: Result (W, L) IV: KPIs	*H2:* It was hypothesized that winning was maximized when PTS > 82, DRB > 28, and TOMARG > -1.7 were achieved for the team of interest.	Conditional inference tree (CIT)
RQ3: Are variations in athlete workload related to pace of play and game outcomes for a specific NCAA Division I WBB Power 4 team?	DV: Result (W, L); PACE IV: KPIs; LOAD; DURATION; ACWR (LOAD); ACWR (D)	*H3:* It was hypothesized that higher levels of LOAD in the 7-day period prior to competition led to a slower PACE and lower odds of winning.	Pearson correlation Independent samples t-test

Note. Research questions for the conducted study. Dependent and independent variables, hypotheses, and analyses plan accompany the research questions.

CHAPTER 4. RESULTS

Chapter 4 includes the results and answers the three research questions of this study. The chapter begins with a discussion of the descriptive and diagnostic analyses of Power 4 conference teams. The chapter transitions into similar methodology relating to the team of interest and concludes with the results of a predictive analysis of the team of interest.

Descriptive and Diagnostic Analysis of Power 4 Conference Teams

Statistical analyses were conducted for Power 4 conference teams, including an overview of records, correlations between KPIs and winning, and a PACE analysis. A panel logit model was then implemented using variables derived from Oliver's Four Factors of winning.

General Records

2128 games were played by teams within the Power 4 conference from 2021-25. Records generated show that the conference had a 1371-757 record (64.4 percent winning percentage) over the four seasons, an average record of 21.4-11.8 per season. The most successful team was 144-7 from 2021-25, a 95.4 percent winning percentage. The least successful program had a record of 52-67 (43.7 percent). There were only 14 instances of losing records in the conference, which represents 21.88 percent of the 64 total team seasons. These numbers are indicative of the conference's strength, which accounted for three of the four NCAA Division I WBB Championships from 2021-25. Table 6 shows a complete breakdown of records, including game type and location.

From a game type perspective, the conference was most successful in nonconference games at 674-165 (80.3 percent). The conference was 151-102 (59.7 percent) in tournament games, winning three national championships and advancing to multiple Sweet 16 and Final Four appearances. Conference games were not included in the game type breakdown as their records are 0.500 because opponents are all in the same conference. A binary logistic regression was conducted with game type as the categorical independent variable and game result (win v. loss) as the binary dependent variable. From the results, winning was significantly higher for nonconference games than tournament games, with the odds of winning a nonconference game 2.8 times higher than the odds of winning a tournament game (Odds Ratio = 2.80, $p < 0.001$).

The average NET for nonconference opponents was 158.24 (Standard Deviation = 109.57, Standard Error = 3.78) but was significantly less for tournament opponents at 42.89 (SD = 43.10, SE = 2.71). The average NET ranking for a conference team was 47.16 (SD = 35.51, SE = 1.10). Lower opponent NET ranks are representative of generally tougher opponents, which more frequently occurred in conference and tournament games. Regardless of opponent strength, the conference still had a winning record across each game type.

Location also played a role in teams' overall winning percentage. Table 6 shows that in home games, the teams were 792-274 (74.3 percent) at home and were 357-347 (50.7 percent) away from home, nearly a losing record. In neutral site games, the teams still had a winning record at 222-136 (62.0 percent). From a binary logistic regression of locational impact on winning, the odds of winning a home game were significantly higher at nearly three times that of an away game (OR = 2.81, $p < 0.001$). Teams in neutral site games had 1.5 times greater odds of winning than teams away from home (OR = 1.59, $p < 0.001$), and home teams' odds were 1.7 times more than teams in neutral site games (OR = 1.77, $p < 0.001$). Overall, the conference was most successful in nonconference games played at home, with significantly higher odds of winning those games than tournament or road games.

Table 6

General Records for Power 4 Conference Teams

Total and Season	Wins	Losses	Winning %
Total Record	1371	757	0.644
Best Total Record	144	7	0.954
Worst Total Record	52	67	0.437
Game Type	**Wins**	**Losses**	**Winning %**
Non-Conference	674	165	0.803
Tournament	151	102	0.597
Location	**Wins**	**Losses**	**Winning %**
Home	792	274	0.743
Away	357	347	0.507
Neutral	222	136	0.620

Note. General records for Power 4 conference teams, accounting for 2128 total games. The table is broken down by total and season records, by game type, and location. The Best Total Record and Worst Total Record each represent the best and worst percentage of total wins versus losses for a particular Power 4 conference team across four seasons.

Descriptive Statistics

Group statistics and independent samples t-tests were conducted to compare mean KPI values between wins and losses. Several KPIs, including PTS, eFG, DRB, and OPP_NET, had significant differences in their means and were labeled as large effects, shown in Table 7. VIF numbers were checked, and 2PT and 3PT were removed as they were highly collinear with FG and eFG. Additionally, TRB represents a case of perfect multicollinearity as TRB = ORB + DRB, so TRB was also removed as a factor. TO were removed due to collinearity with TOMARG.

In general, winning teams demonstrated a higher effective field goal percentage at 51.0 percent in wins versus 42.0 percent in losses. Additionally, wins were impacted by higher rebounding margins at 9.59 in wins versus -5.84 in losses and a plus turnover margin at 2.89 in wins versus -1.25 in losses. From a basic statistical overview of the 2128 games, shooting efficiency, rebounding, and turnovers had significant differences between wins and losses (see Table 7). These variables represent three of the Four Factors, characterized by Oliver (2004). Shooting efficiency, rebounding, turnovers, and free throws drove the creation of the game model from the panel logit conducted, discussed in the diagnostic analysis section of the results section.

PACE Analysis

Pace of play (PACE) shapes game control in basketball and is calculated as the average number of possessions per 40 minutes, or a complete game. More possessions are indicative of a faster PACE, and fewer possessions are indicative of slower PACE. This study investigated the impact of varying levels of PACE on game outcomes. Reasoning was derived from the team of interest, who ranked first or third in three of the last four seasons at an average PACE of 81.27. The team of interest stated that their system relied heavily on their PACE, focusing on up-tempo and efficient shots. Translating this to the rest of the conference was a focus of H2 for RQ2, which discussed the expectation that differences in KPIs would result from the stratification of teams based on PACE. Table 8 shows the statistically significant association of PACE with TO, PTS, and FG, further justifying the potential stratification of teams by PACE. While PACE generally led to more TO, PTS, and increased FG within a game, PACE was not a primary driver of success of a game. Based these analyses, stratification by PACE was not necessary to inform the study's conclusions.

Table 7

Descriptive Statistics of KPIs in Wins and Losses

KPI	Mean ± SD	Wins	Losses
PTS	72.79 ± 14.48	78.71 ± 12.70	62.08 ± 10.93
FG	0.43 ± 0.07	0.46 ± 0.06	0.38 ± 0.06
eFG	0.48 ± 0.09	0.51 ± 0.08	0.42 ± 0.07
DRB	24.31 ± 5.85	26.26 ± 5.57	20.78 ± 4.54
REBMARG	4.10 ± 12.69	9.59 ± 10.50	-5.84 ± 9.98
PAINT	33.75 ± 10.97	37.12 ± 10.69	27.63 ± 8.55
AST	14.53 ± 5.22	16.26 ± 5.04	11.38 ± 3.89
OPP_NET	90.45 ± 92.51	120.28 ± 99.83	36.43 ± 38.52
ORB	11.08 ± 4.64	12.08 ± 4.77	9.28 ± 3.76
TOMARG	1.42 ± 6.37	2.89 ± 6.30	-1.25 ± 5.58
STL	8.36 ± 3.84	9.06 ± 4.00	7.11 ± 3.16
BLK	4.25 ± 2.76	4.78 ± 2.920	3.28 ± 2.13
PF	16.89 ± 4.43	16.01 ± 4.24	18.48 ± 4.33
FT	0.71 ± 0.12	0.71 ± 0.12	0.69 ± 0.14
PACE	73.59 ± 6.48	73.66 ± 6.51	73.46 ± 6.43

Note. Descriptive statistics of KPIs for Power 4 conference teams. Pooled means and standard deviations are included in the table.

Table 7 provides that the mean PACE was 73.66 in wins and 73.46 in losses, a mere 0.20 difference. In addition, a chi-square test of independence was conducted to measure the strength of the association between average PACE (low, medium, and high), resulting in a Cramér's V of 0.124, with $p < 0.001$. Although the association was statistically significant, the effect size between PACE group and game result was small. From these two analyses, PACE alone explains a limited amount of variability in game outcome, indicating limited practical significance in the context of this study. PACE is shared by both teams within each game, and efficiency may be more indicative of success, especially in a conference that is generally equal in strength from the best to worst teams. Although PACE was not statistically significant on its own, it was retained in the full model to ensure a comprehensive representation of team performance.

Table 8

PACE Correlations

IV	DV	R	R^2	P-value
PACE	TO	0.32	0.10	< 0.001
PACE	PTS	0.48	0.23	< 0.001
PAINT	FG	0.62	0.39	< 0.001

Note. Correlations between PACE and TO, PTS, and FG.

Panel Logit

A panel logit was conducted to uncover the key performance indicators of success across the Power 4 conference. The full performance model of the KPIs in Table 7 was estimated using panel regression methods in the *plm* package in R. To account for unobserved heterogeneity at the Team_Year level, both fixed effects and random effects specifications were estimated. The Team_Year captures unobserved factors affecting performance within a given team in a specific season, including roster composition, coaching strategy, injuries, team culture, and other characteristics not explicitly defined in the model. There were 64 Team_Year fixed effects, based on the 16 Power 4 conference teams across four seasons (16 times 4).

A Hausman test was conducted to assess whether the unobserved Team_Year effects were correlated with the KPIs. The null hypothesis states that the Team_Year effects are uncorrelated with the KPIs, implying that the random effects estimator is consistent (Baltagi, 2014). Using the *phtest* function, the fixed effects model was compared to the random effects model. The test results led to the rejection of the null hypothesis ($\chi^2 = 139.85$, df = 19, $p < 0.001$). Thus, the unobserved Team_Year effects are correlated with the KPIs, so the random effects estimator would be an inconsistent model. The fixed effects specification was selected as the preferred model.

The NET ranking variable was removed from the model due to collinearity. One Team_Year fixed effect (38 observations) was dropped as that team's season record was 38-0, which is perfect prediction. The fixed effects logit estimation requires within-group variation in the binary dependent variable. The adjusted pseudo R^2 value and squared correlation for the full model indicated strong predictive alignment and goodness-of-fit for the model ($R^2 = 0.71$, Squared Correlation = 0.80).

In the full model, OPP_NET, PACE, eFG, FT, DRB, REBMARG, STL, TOMARG, and PF were statistically significant based on p-values. Odds ratios were greatest for eFG at 4.14, TOMARG at 1.56, DRB at 1.46, and REBMARG at 1.16, increasing the odds of winning with a one-unit increase in each KPI. Based on the Four Factors framework defined by Oliver (2004), the full performance model was reduced to OPP_NET, eFG, TOMARG, REBMARG, and FT as KPIs.

The reduced performance model was run with fixed effects through the *feglm* package in R. The model is represented in Equation (2).

$$\text{logit}(P(\text{WIN}_{it} = 1)) = \beta_0 + \beta_1\text{OPP\_NET}_{it} + \beta 2\text{eFG}_{it} + \beta_3\text{TOMARG}_{it} + \beta_4\text{REBMARG}_{it} + \beta_5\text{FT}_{it} + \beta_6\text{PF}_{it} + \alpha_{iy} \quad (2),$$

where:

$\text{WIN}_{it} = 1$ if team i wins game t, 0 otherwise;

OPP_NET_{it} = Opponent NET ranking for team i for game t;

eFG_{it} = Effective field goal percentage;

$TOMARG_{it}$ = Turnover margin;

$REBMARG_{it}$ = Rebound margin;

FT_{it} = Free throw percentage;

PF_{it} = Personal fouls;

α_{iy} = Team_Year fixed effect.

The reduced Four Factors model improved parsimony, avoided overfitting, and increased interpretability. Table 9 and Figure 3 show the point estimates and odds ratios for each KPI in the model. While the fit statistics decreased ($R^2 = 0.50$, Squared Correlation = 0.75), the most impactful KPIs were included in the reduced model based on an established theoretical framework in the Four Factors.

Table 9

KPIs in the Four Factors Reduced Model

KPI	Point Estimate	95% CI	Odds Ratio	P-value	Interpretation
TOMARG	0.556	(0.376, 0.735)	1.743	< 0.001	74.3% higher odds
eFG	0.328	(0.257, 0.399)	1.388	< 0.001	38.8% higher odds
REBMARG	0.275	(0.189, 0.361)	1.317	< 0.001	31.7% higher odds
FT	0.082	(0.044, 0.120)	1.085	< 0.001	8.5% higher odds
OPP_NET	0.015	(-0.006, 0.036)	1.015	0.172	1.5% higher odds
PF	-0.208	(-0.428, 0.011)	0.812	0.063	18.8% lower odds

Note. Point estimates, 95% confidence intervals, odds ratios, and p-values are reported from the panel logit model of KPIs in the reduced Four Factors model for Power 4 conference teams. The odds ratios represent the change in odds of winning associated with a one-unit increase in each KPI. All KPIs, except OPP_NET and PF, were statistically significant with game outcome ($p < 0.05$).

Odds ratios found in Table 9 indicate that TOMARG, eFG, and REBMARG are influential as determining factors of winning. A one-unit increase in TOMARG increased the odds of winning by 74.3 percent, or 1.743 times higher odds (OR = 1.743, $p < 0.001$). Turnovers occur frequently in basketball, making possession control a central aspect of the game. This finding aligns with the NFL study by Gifford and Bayrak (2023). Their NFL analytics model found that a one-unit increase in defensive turnovers led to 2.49 times higher odds of winning (Point estimate = 0.912, OR = 2.49). In sports with fewer scoring opportunities, such as football, turnover-related advantages may have even larger impacts. Nevertheless, TOMARG remains a critical determinant of basketball outcomes due to the high frequency and variability of turnovers across games.

Although football and basketball differ in gameplay, strategy, personnel, and various on-court and field aspects, it is clear between these two studies that ball control is crucial to success. Limiting turnovers and forcing opponent turnovers influences turnover margin and ball security. In leagues such as the NFL or this Power 4 conference, the margin for error is small. With 248 one or two possession games (23.9 percent of all conference games) between equally strong teams since 2021, forcing or conceding a turnover may be the difference between a win and loss. Based on this model, the odds of winning a game increased by 74.3 percent for every defensive turnover forced or offensive possession ending without a turnover.

Shooting efficiency (eFG), rebounding (REBMARG), and free throws (FT) are other factors represented in the model that increased the odds of winning. With a one-point increase in eFG (i.e., 0.01), the odds of winning increased by 38.8 percent, a one-unit increase in REBMARG corresponded with a 31.7 percent increase, and a one-unit increase in FT led to an 8.5 percent increase in the odds of winning. Oliver’s Four Factors framework clearly translates to the WBB game, with shooting efficiency, rebounding, turnovers, and free throws identified as KPIs of winning across Power 4 conference teams.

Predictive Analysis for Team of Interest

Analyses for all 16 Power 4 conference teams were repeated for the team of interest. In addition, a training load analysis was conducted, and conditional inference trees were created for deeper practical insights.

General Records

Records generated show that the team of interest had a 101-34 record (74.8 percent) from 2021-25. The team of interest was most successful in the 2021-22 season, with a record of 26-7 (78.8 percent). The team was least successful by record in the 2023-24 season at 23-10 (69.7 percent), despite winning a Power 4 Conference Championship in the same season. Table 8 shows a complete breakdown of records, including game type and location.

From a game type perspective, the team of interest was most successful in nonconference games at 39-8 (83.0 percent), then conference games at 52-18 (74.3 percent), and tournament games at 10-8 (55.5 percent). This is indicative of a stronger strength of schedule for the team of interest in conference and tournament games than in nonconference games. A binary logistic regression was conducted between game type and result. From the results, winning was significantly higher for nonconference games than tournament games, with the odds of winning a nonconference game 3.9 times higher than the odds of winning a tournament game (Odds Ratio = 3.90, $p = 0.03$). There was nonsignificant difference between nonconference and conference games as well as conference and tournament games, respectively.

The average NET for nonconference opponents was 81.04 ($SD = 91.70$, $SE = 9.46$) but considerably less for conference opponents at 39.66 ($SD = 30.51$, $SE = 2.58$) and tournament opponents at 34.11 (SD = 27.63, SE = 4.60). Lower opponent NET ranks are representative of generally tougher opponents, which the team of interest faced more frequently in conference and tournament games. Regardless of opponent strength, the team of interest still had a winning record in each game type.

Location also played a role in the team's overall winning percentage. Table 10 shows that the team of interest was 55-10 (84.6 percent) in home games and was 34-14 (70.8 percent) away from home. In neutral site games, the team still had a winning record at 12-10 (54.5 percent). From a binary logistic regression of locational impact on winning, the odds of winning a home game were 2.27 times higher than an away game but at a statistically insignificant level (OR = 2.27, p = 0.08). Significant were the 4.58 times greater odds of winning a home game than a neutral game for the team. Similarly to the game type variable analysis, the team of interest had a winning record at each location. Overall, the team of interest was 101-34, with nonconference and home games representative of the most success.

Descriptive Statistics

Similar methodology from the Power 4 conference analysis to calculate group statistics and conduct independent samples t-tests was followed for the team of interest. Several KPIs, including PTS, eFG, DRB, and OPP_NET, had significant differences in their means and were labeled as large effects, shown in Table 11. This is similar to the Power 4 conference teams profile, but the average PTS and PACE were significantly higher in mean value. Overall, the most impactful KPIs in wins versus losses for the team of interest closely followed the Four Factors model as expected. In wins, the team of interest scored about 14 more PTS, had 8 percent better eFG, a large REBMARG, and a positive TOMARG, in comparison to losses. The distribution of PTS, PF, and REBMARG in wins versus losses are shown in Appendix B Figures B1-B3, further illustrating the results of the CITs in Figures 4-6.

Table 10

General Records for Team of Interest

Total and Season	Wins	Losses	Winning %
Total Record	101	34	0.748
Best Record	26	7	0.788
Worst Record	23	10	0.697
Game Type	**Wins**	**Losses**	**Winning %**
Non-Conference	39	8	0.830
Conference	52	18	0.743
Tournament	10	8	0.555
Location	**Wins**	**Losses**	**Winning %**
Home	55	10	0.846
Away	34	14	0.708
Neutral	12	10	0.545

Note. General records for the team of interest, accounting for 135 total games. The table is broken down by total and season records, by game type, and location. The Best Total Record and Worst Total Record each represent the best and worst percentage of total wins versus losses in a particular season for the team of interest, respectively.

PACE Analysis

As stated in the Power 4 conference analysis, the team of interest had a consistently high PACE, at 81.27 on average, first in Division I WBB two of last four years. While a statistic that is unique to the team of interest, PACE was not found to be significantly associated with game result. In wins, the team of interest had an average PACE of 80.94 and an average PACE of 80.72 in losses. From an independent samples t-test, with equal variances assumed, $p = 0.69$ between PACE and game result. Thus, PACE is statistically insignificant as a sole indicator of success for the team of interest.

Table 11

Descriptive Statistics of KPIs for Team of Interest in Wins and Losses

KPI	Mean ± SD	Wins	Losses
PTS	82.01 ± 13.07	85.62 ± 11.34	71.26 ± 12.02
FG	0.44 ± 0.07	0.46 ± 0.06	0.39 ± 0.06
eFG	0.51 ± 0.08	0.53 ± 0.07	0.45 ± 0.07
DRB	28.15 ± 5.88	29.39 ± 5.60	24.47 ± 5.15
REBMARG	6.94 ± 11.40	9.48 ± 10.90	-3.90 ± 9.49
PAINT	36.59 ± 8.86	38.59 ± 8.56	30.65 ± 6.94
AST	20.37 ± 5.16	21.62 ± 4.57	16.65 ± 5.10
PF	18.93 ± 4.43	18.16 ± 4.22	21.24 ± 4.31
OPP_NET	53.47 ± 62.54	95.59 ± 83.64	26.00 ± 38.74
TOMARG	-1.73 ± 6.18	-0.60 ± 6.01	-5.06 ± 5.52
FT	0.73 ± 0.10	0.74 ± 0.09	0.72 ± 0.13
ORB	11.32 ± 4.17	11.62 ± 4.37	10.41 ± 3.41
STL	8.73 ± 3.42	9.14 ± 3.47	7.53 ± 3.02
BLK	3.56 ± 2.12	3.80 ± 2.12	2.82 ± 1.98
PACE	81.27 ± 6.75	81.40 ± 6.75	80.87 ± 6.85

Note. Descriptive statistics of KPIs for the team of interest. Pooled means and standard deviations are included in the table.

While PACE does not significantly impact wins versus losses, turnovers and player load metrics are directly correlated with PACE. Table 12 shows the associations related to PACE and player load. A higher PACE implies more possessions, which leads to more TO ($R = 0.40$, $p < 0.001$). ACWR (LOAD) was negatively associated with PACE ($R = -0.20$, $p = 0.048$) and TO ($R = -0.08$, $p = 0.43$). This impact was statistically significant for PACE, indicating that a spike in recent training volume may have elicited greater fatigue, which led to a slower PACE during gameplay. Thus, a more “trained” team of interest, with a greater acute to chronic workload ratio, had a slower PACE and fewer TO. With these insights, it is important to consider that an even more robust training regimen in days closest to competition did not have a significant impact on game outcome, just the within-game KPIs of PACE and TO.

Table 12

PACE and Training Load Correlations

IV	DV	R	R^2	P-value
PACE	TO	0.40	0.16	< 0.001
ACWR (LOAD)	PACE	-0.20	0.04	0.048
ACWR (LOAD)	TO	-0.08	0.01	0.431
ACWR (LOAD)	ACWR (D)	0.74	0.55	< 0.001
LOAD	DURATION	0.80	0.64	< 0.001

Note. Correlations between PACE, TO, LOAD, DURATION, ACWR (LOAD), and ACWR (D). PACE and TO were recorded in all 135 games. ACWR (LOAD) and ACWR (D) were recorded in 103 games, and LOAD and DURATION were recorded in 35 games.

Conditional Inference Trees (CITs)

The descriptive statistics included in Table 11 and the PACE correlations in Table 12 provide an overview of the impactful KPIs that determined the records listed in Table 10. For deeper practical insights, CITs were created to establish statistical thresholds that accounted for the greater percentage of wins across the 2021-25 seasons, following the methodology of Leicht et al. (2017). The CITs provide a stable, interpretable winning profile and relationship that generalizes across seasons. Based on the nodes of the tree, these KPIs are identified. The data was split into two, with one set of trees representing the statistical thresholds for the team of interest to reach, and the other set representing the opponent. A significance level of 0.05 was used to create a conservative tree and prevent overfitting, while 0.10 was used for a more exploratory analysis.

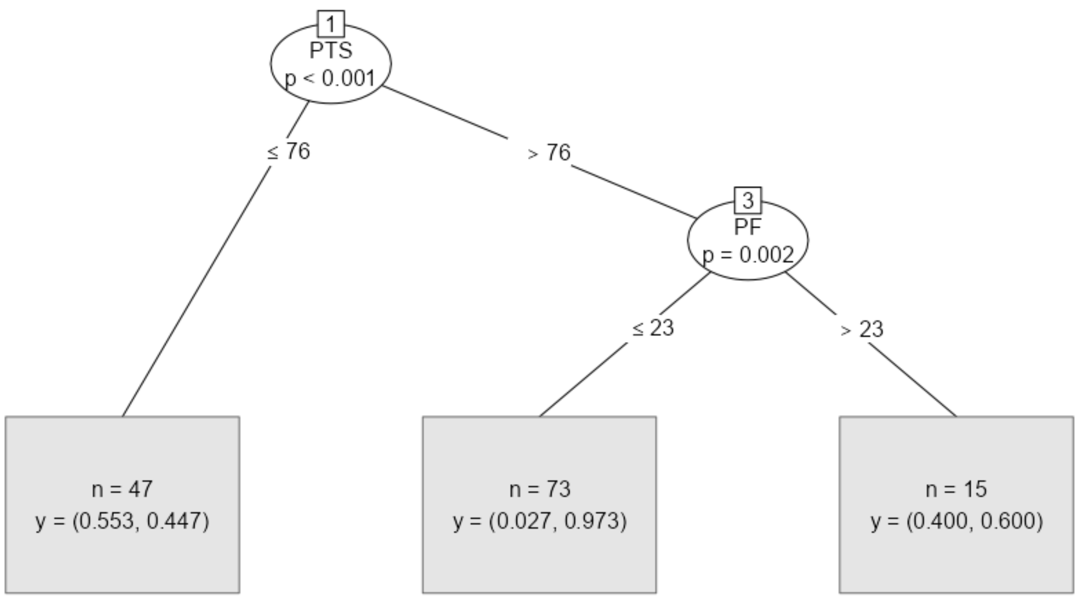
Figure 3 represents the most conservative CIT, at an alpha level of 0.05. The ovals represent the nodes where the algorithm tested a KPI to split the data if $p < 0.05$ and include the predictor variables. The topmost oval shows the most impactful KPI on winning and the subsequent node(s) represents additional predictors. The boxes represent the terminal nodes, with *n* indicating the number of games in the subgroup, and *y = (percentage of games lost, percentage of games won).* The CIT analysis indicates that the team of interest won 97.3 percent of their games when they scored more than 76 points were scored and less than or equal to 23 fouls were committed (Figure 3). In contrast, the team of interest scored less than 76 points in 47 games, which resulted in a 44.7 percent winning percentage. Thus, scoring at least 76 points and committing less than 23 fouls maximized the likelihood of winning for the team of interest from 2021-25.

Similarly, a CIT at an alpha level of 0.10 represents a more exploratory analysis of wins and losses to include additional KPIs. The same combination of PTS and PF is included in the CIT shown in Figure 4, but a unique combination of PTS, PF, and REBMARG yielded a perfect win rate. While only accounting for 9 of the 135 games, scoring greater than 76 points, committing greater than 23 fouls, and outrebounding the opponent by at least 2 was the optimal formula for success.

It is also important to consider what statistical markers lead to the most success for opponents against the team of interest. What statistics the team of interest must limit for an opponent to maximize their likelihood of winning is a key consideration. Figure 5 depicts this idea at an alpha level of 0.05. The boxes still represent the terminal nodes, and *y = (percentage* *of games the team of interest lost, percentage of games the team of interest won)*. When the team of interest limited opponents under 44.6 percent field goals and allowed less than or equal to 26 defensive rebounds, the team of interest won 94.9 percent of the 51 games accounted for. Similarly, the unique combination of less than 44.6 percent FG, greater than 26 DRB, and a near negative turnover margin (< 2) yielded 88.2 percent of games won.

Figure 3

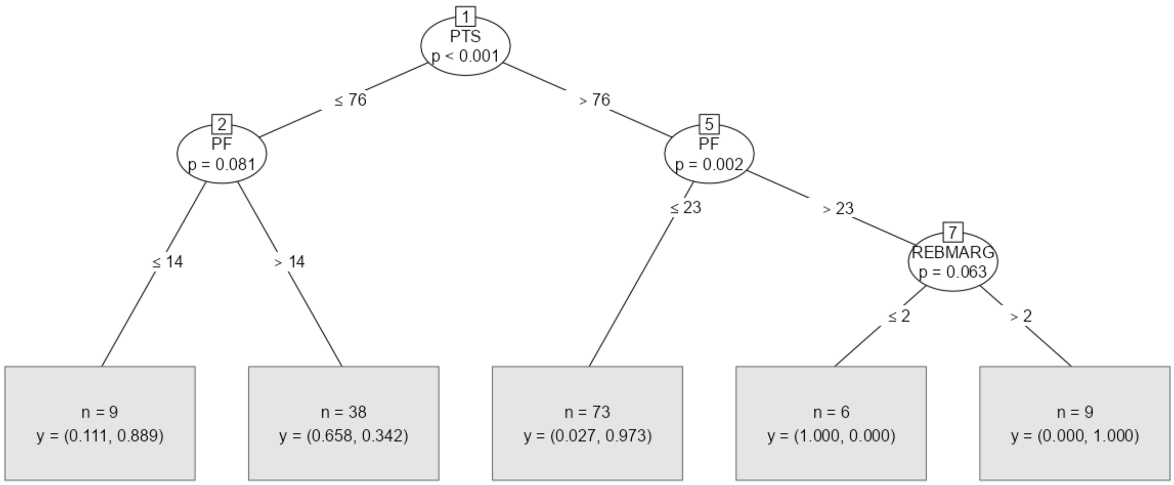
CIT for Team of Interest (P < 0.05)



Note. CIT for the team of interest at an alpha level of 0.05. The root node is PTS with a subsequent node of PF (ovals). The terminal nodes (boxes) show the number of games in each subgroup and percentage of games lost and won.

Figure 4

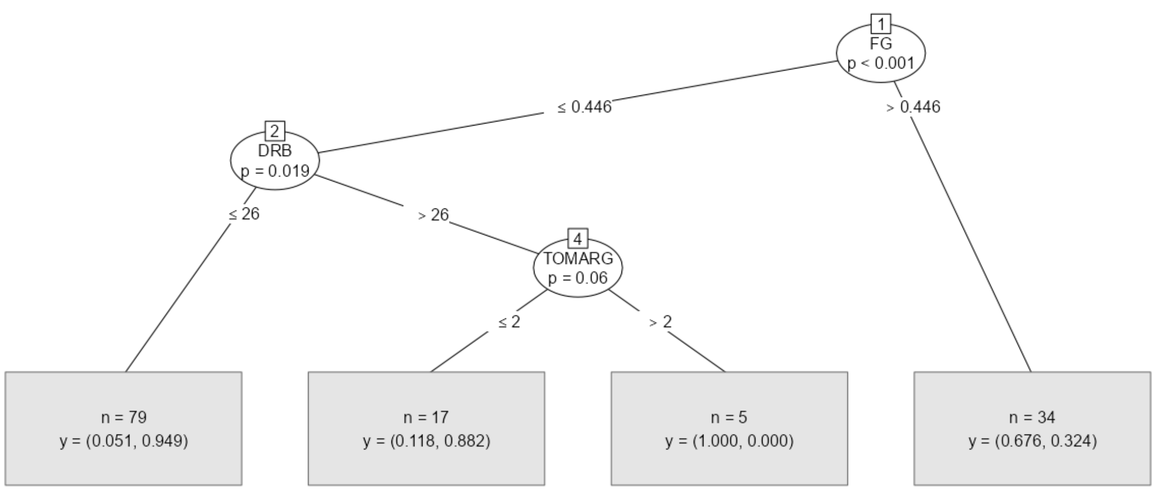
CIT for Team of Interest (P < 0.10)



Note. CIT for the team of interest at an alpha level of 0.10. The root node is PTS with subsequent nodes of PF and REBMARG (ovals). The terminal nodes (boxes) show the number of games in each subgroup and percentage of games lost and won.

Figure 5

CIT for Opponents (P < 0.05)



Note. CIT for opponents at an alpha level of 0.10. The root node is PTS with subsequent nodes of DRB and TOMARG (ovals). The terminal nodes (boxes) show the number of games in each subgroup and percentage of games lost and won.

The CIT provides a practical solution for coaches to say, *"when we do X, we almost always win."* For example, *"when the team of interest scores at least 76 points and commits less than 23 fouls in a given game, they win 97.3 percent of the time."* The CIT supports the theory of the Four Factors by providing a structured model for the team of interest to follow to maximize the likelihood of winning. Focusing on shooting efficiency, rebounding, and limiting turnovers yielded the highest probabilities of success in the CIT, indicating that optimizing these KPIs yield the greatest impact on game outcome. The distributions of PTS, PF, REBMARG for the team of interest and DRB, FG, and TOMARG for the team's opponent for wins and losses are shown in Figures B1-B6 in Appendix B.

CHAPTER 5. DISCUSSION

Chapter 5 discusses how the study answered the research questions introduced in Chapter 1. The chapter begins by addressing RQ1, RQ2, and RQ3 and the hypotheses. The section also presents the key findings, their significance, and practical implications. The chapter concludes with the limitations of the data and potential areas of future research.

Research Questions

The data analysis plan outlined in Table 5 includes the three research questions for this study. Pearson correlations, independent samples t-tests, panel binary logits, and CITs were primary methods for addressing these questions. To address RQ1, teams were stratified into low, moderate, and high levels of PACE. It was hypothesized that for teams with high and moderate levels of PACE, PTS, TRB, and TO were the key performance indicators associated with winning. For teams with low levels of PACE, PTS, TRB, opponent FG, and opponent 3PT were the key performance indicators of winning (H2). Pearson correlations and Cramér's V revealed that while statistically significant, the difference in wins versus losses in PACE based on stratification was not necessary. The average PACE between wins and losses only differed by 0.20, far less than a possession per game. H1 was not supported.

The results did not support H1 as margins were more influential on winning than raw KPIs. After conducting statistical analyses, TOMARG, REBMARG, and eFG were identified as three impactful KPIs on winning for the Power 4 conference teams studied. For the team of interest, these KPIs were also influential as well as PTS, PF, defensive FG, and opponent DRB. These results align well with Oliver's Four Factors model, discussed further in the key findings section.

The creation of CITs was used to test H2 for RQ2. H2 proposed that winning was maximized when the following performance thresholds were achieved for the team of interest: PTS > 82, DRB > 28, and TOMARG > -1.7. The findings partially support H2. PTS emerged as the root node of the CIT, with a threshold of PTS > 76 serving as the primary decision criterion in the CIT analysis. Opponent FG served as the root node and primary criterion for the opponent's CIT in Figure 5, with FG ≤ 44.6 percent as a determining factor in wins versus losses. PTS > 76, PF ≤ 23, REBMARG > 2, opponent FG ≤ 44.6, opponent DRB ≤ 26, and opponent TOMARG ≤ 2 were identified as the primary decision thresholds in predicting game outcomes.

RQ3 was addressed by conducting Pearson correlations between LOAD, DURATION, ACWR (LOAD), and ACWR (D), with PACE, TO, and game outcome. H3 predicted that higher levels of LOAD in the 7-day period prior to competition would lead to a slower PACE and lower odds of winning. This hypothesis was partially supported. ACWR (LOAD) was negatively correlated with PACE, indicating that a higher acute-to-chronic workload ratio was associated with lower PACE. Across the 35 games analyzed with these measures and 103 games including both ACWR variables, patterns in PACE were evident. However, there was no clear evidence that either LOAD or DURATION significantly influenced the odds of winning.

Key Findings

Competitive Power 4 Conference

There were several key findings that add significance to WBB analytics. First, this research revealed that the 16 Power 4 conference teams studied were highly competitive in the NCAA Division I landscape from the 2021-25 seasons. Achieving an overall winning percentage of 64.4 percent through 2128 total games and accounting for three of the four National Championships in those seasons demonstrates this fact. Additionally, 248 (23.9 percent) of the conference games were decided by one or two possessions, indicating the competitive balance of the Power 4 conference. The teams were most successful in home and nonconference games, with the odds of winning home versus away games (OR = 2.81) and nonconference versus tournament games at nearly three times each (OR = 2.80). Location and game type were major influencers in the overall record of the Power 4 conference teams.

KPIs of Winning and Four Factors

Second, the results of t-tests revealed that several KPIs, including eFG, REBMARG, and TOMARG, had significant differences in wins versus losses. These KPIs served as the basis for the panel logit conducted in this study, based on the theoretical Four Factors framework created by Dean Oliver (2004). The reduced model with fixed effects was represented in Equation (2), shown below.

$$\text{logit}(P(WIN_{it} = 1)) = 0.015*OPP\_NET_{it} + 0.328*eFG_{it} + 0.556*TOMARG_{it} + 0.275*REBMARG_{it} + 0.082*FT_{it} + -0.208*PF_{it} + \alpha_{iy} \quad (2)$$

Model parsimony and accuracy were achieved based on the fit statistics ($R^2 = 0.65$) and included the following KPIs: OPP_NET, eFG, TOMARG, REBMARG, FT, PT, and the Team_Year fixed effects variable. Significant odds ratios of 1.743, 1.388, and 1.317 for TOMARG, eFG, and REBMARG, respectively, models three of Oliver's Four Factors.

For every one-unit increase in TOMARG (turnovers), the odds of winning increased by 74.3 percent. For every one-unit increase in eFG (shooting efficiency), the odds of winning increased by 38.8 percent. In addition, every one-unit increase in REBMARG (rebounding), the odds of winning increased by 31.7 percent. FT led to an 8.5 percent increase in the odds of winning, and PF 18.8 percent lower odds of winning with every one-unit increase in each KPI.

Playing higher ranked, or generally weaker opponents, also led to a 1.5 percent increase in odds of winning for every rank increase in NET for opponents.

Shooting efficiency (eFG), rebounding (REBMARG), turnovers (TOMARG), and free throws (FT) are KPIs represented in the model that increased the odds of winning. These represent all of Oliver's Four Factors. The results of the panel logit demonstrate that the Four Factors framework is important in determining WBB game outcomes. Shooting efficiency, rebounding, turnovers, and free throws were identified as KPIs of winning across Power 4 conference teams.

Insignificant PACE Impact on Result

Another key finding of this study is that PACE is not a relevant determining factor in game outcome across the Power 4 conference. Average PACE only differed by 0.20, or far less than a possession, in wins versus losses. While PACE has a strong association with in-game statistics, including TO, PTS, and FG, PACE has a small association with game outcome. Stratifying teams into groups based on low, moderate, and high PACE levels demonstrates this fact with a Cramér's $V = 0.124$ and $p < 0.001$. PACE alone explains a limited amount of variability in game outcome, and efficiency metrics are more indicative of success. In a conference of this caliber where the margin for error is small, efficiency is crucial.

The results of the PACE analysis closely mirror the results of a similar analysis conducted for the team of interest. Ranked first in Division I WBB in PACE at an average of 81.27 per game in two of the four seasons studied, the team of interest's PACE was considered an impactful KPI on game outcome prior to this study. Based on the results, the team of interest did not have significant differences in average PACE between wins (80.94) and losses (80.72), with $p = 0.97$. A higher PACE is indicative of more possessions, which leads to more TO (R =

0.40, $p < 0.001$), consistent with the results of all the Power 4 conference teams. In-game statistics, including TO, PTS, and FG were correlated with PACE, but PACE did not significantly impact the overall success of the team of interest based on game outcome.

Training Load

PACE was not a significant KPI in distinguishing wins versus losses, but it was closely associated with the ACWR (LOAD) variable. ACWR (LOAD) was negatively associated with both PACE and TO; the correlation was significant ($R = -0.20$, $p = 0.04$) but not for TO ($R = -0.08$, $p = 0.43$). It is evident that the timing and volume of training impacted PACE but not TO. During the study period, spikes in recent (acute) training volume contributed to greater fatigue, resulting in slower PACE. While a more robust training design did not significantly affect game outcomes, it did impact pace of play for the team of interest.

Team of Interest Success

The team of interest was more successful than the average Power 4 conference team in the 2021-25 seasons, with an overall winning percentage of 74.8 percent, approximately 10 percent greater than the average team. Similarly to the Power 4 conference, the team of interest won 84.6 percent of their home games and 83.0 percent of their nonconference games. The odds of winning a nonconference game were 3.9 times higher than a tournament game ($OR = 3.90$, $p = 0.03$), and there was minimal difference in the odds of winning between nonconference and conference games. In addition, the odds of winning a home versus an away game were 2.27 times higher and statistically significant ($OR = 2.27$, $p = 0.08$). The team of interest was most successful in home and nonconference games like the Power 4 conference overall, indicating that location and game type influence win rates.

Statistical Thresholds for Team of Interest

For the team of interest, there were large differences in mean values for several KPIs, including PTS, eFG, REBMARG, and OPP_NET, consistent with the Four Factors model for the Power 4 conference teams of study. The average PTS in wins were approximately 86 and 69 in losses, and the average FG in wins were 46 percent and 38 percent in losses ($d = 1.49$), shown in Table 10. It is unsurprising that PTS and FG emerged as the root nodes for the CITs that were created for the team of interest and their opponents. Figure 3 represents the CIT for the team of interest at an alpha level of 0.05. A unique combination of PTS > 76 and PF ≤ 23 yielded a 97.3 winning percentage for the team of interest. Winning percentage decreases significantly to 44.7 percent if PTS ≤ 76, or to 60.0 percent if PF > 23 (Figure 3).

At an alpha level of 0.10, the results are more exploratory but still are consistent and add in REBMARG as a decision criterion. PTS > 76, PF > 23, and REBMARG > 2 yielded a perfect win rate for 9 of the 135 games. While this combination represents 6.7 percent of all games (Figure 4) and even with a large number of fouls committed (PF), it shows coaches that there are multiple ways to win. The predictive power of CITs and their associated practical implications are discussed in the next section.

Identifying which opponent KPIs must be limited to increase the likelihood of winning represents a crucial determinant of success. When opponents were limited to < 44.6 percent FG and grabbed ≤ 26 DREB, the team of interest won 94.9 percent of the games. The team of interest won 88.2 percent of games when the following thresholds were achieved: < 44.6 percent FG, > 26 DRB, and < 2 TOMARG. Shooting efficiency, rebounding, and turnovers were major components of the CITs, another layer of evidence to support the Four Factors model in WBB.

Practical Implications and Significance

Four Factors

The results of this study demonstrate measurable predictive utility. For a Division I WBB coach, the panel logit demonstrates that the difference between wins and losses in a Power 4 conference is largely due to shooting efficiency, rebounding, and turnovers. These represent three of Oliver's Four Factors. While this study does not implement the approximate weights that are assigned to each factor by Oliver, it does imply that a coach should highly consider a game strategy based on the Four Factors. The same question posed by Oliver – *"How do basketball teams win games?"* – is addressed by the results of the panel logit. Effective field goal percentage (eFG), turnover margin (TOMARG), and rebounding margin (REBMARG) are three KPIs included in this study's reduced Four Factors model. These three KPIs are critical in achieving wins versus losses and must be the focus of any coach serious about competing at the highest level in NCAA Division I WBB. This model serves as the foundation for developing a game model of success in WBB.

Predicting Game Outcome

The reduced Four Factors model underscores the effectiveness of a data-driven strategy in WBB. The results from the CITs of this study further reinforce this concept. Coaches can use the CITs to produce statistical game plans based on the decision criterion thresholds. For the team of interest, game strategy can be tailored to ensure the following unique combination of KPI values are achieved:

1. Points > 76 + Personal Fouls ≤ 23

   = 97.3 winning percentage

2. Opp. Field Goal Percentage < 44.6 percent FG + Opp. Defensive Rebounds ≤ 26

= 94.9 percent winning percentage

These are clear markers for the coaches of the team of interest to follow to maximize their likelihood of winning a given game. Training design, game preparation, in-game adjustments, recruiting, and athlete evaluation should be shaped by these thresholds. In particular, training design can focus on the skills and strategies strongly associated with success, while game preparation and in-game adjustments can exploit opponent weaknesses revealed by analytics, such as FG and DREB. Recruiting decisions can prioritize athletes who shoot efficiently and excel in defense and rebounding. By aligning recruits' performance profiles with winning-based KPIs, coaches can implement an effective, data-driven approach to athlete evaluation.

The CIT thresholds may vary across years and teams as personnel, team dynamics, and other factors change, but they can be adapted to other seasons and teams. With any team's dataset, this study can be replicated to uncover the specific KPI thresholds that maximize winning for that team. Through the application of these thresholds in coaching practices, teams can make data-informed decisions that enhance performance and improve resource allocation, resulting in a competitive advantage on and off the court. These numbers are undeniably important to any coaches' game strategy and should be incorporated as a focal point to achieve sustained success in the NCAA Division I WBB landscape.

Expansion of WBB Analytics

The results of this study are notable as no previous study has developed a game model or established statistical thresholds for success in collegiate WBB. Leicht et al. (2017) evaluated Olympic WBB using similar methodology, Juliano and Thakker (2023) tracked a team's performance data over the course of season, and Tomanek et al. (2025) studied Men's Olympic

Tournaments. These studies, along with Gifford and Bayrak (2023) provided the framework for this study to follow, but analytics were explored in a new context: women's college basketball. The results of this study are invaluable and serve as the foundation for further research into the data-driven, analytical component of WBB. As the game continues to grow and evolve at the national and international levels, research in WBB analytics, especially in college WBB, is critical for coaches seeking to improve performance and gain a competitive advantage.

Limitations of Data

The data has a few limitations that may have led to minor variations in results compared to a study using similar methodology. The sample is one Power 4 conference, and it was highly successful from 2021-25 at a 64.4 winning percentage and three National Championships in four years. The primary limitation is that the findings may not generalize beyond the sample. Additionally, the NET ranking was recorded at the end of the season. While there are changes that occur throughout the season, this provided a limited but useful profile of the strength of a given team.

Sports science data, including player and duration, were limited in observation numbers but were not the emphasis of this study. From a team perspective, two of the Power 4 conference teams, including the team of interest, transitioned from a different Power 4 conference prior to the 2024-25 season. This may have resulted in a small variation in results, but it was unlikely to be significant as Power 4 conferences represented the highest level of competition in WBB. Overall, differences in wins and losses are still explained by the Four Factors, and these limitations did not diminish strength or practical significance of the study's findings.

Conclusion and Future Research

This study provides a foundational approach to developing a game model of success in college WBB, offering valuable insights into the team-level performance within a Power 4 conference from 2021-25. Three primary research questions examined the impact of PACE, key performance indicators (KPIs), and athlete training load on game outcomes in NCAA Division I WBB. The findings indicate that while PACE and training load influence other team-level KPIs, they are not the most influential factors in winning. Overall, the results support Oliver's Four Factors framework, identifying shooting efficiency, rebounding, and turnovers as key determinants of winning.

Coaches should prioritize the optimization of efficiency-based metrics and apply KPI thresholds to inform game strategy, training design, and recruiting decisions. By aligning performance objectives with these KPIs, programs can improve decision-making and increase the likelihood of winning. A visual summary is provided in Appendix B (Figure B7).

Future research should build upon the established methodology and model established through RQ1-RQ3. Incorporating player-level data may provide insights into how individual contributions influence team success. Moreover, the game model could be enhanced by integrating spatial, film, and live analytical analyses, including shot chart creation, off-ball movement modeling, and in-game statistical tracking. Including advanced metrics, such as lineup combinations and efficiency, alongside character, culture, and psychometric measurables, may deepen the analysis. Comparative studies across teams and conferences could also help identify strategic patterns associated with the highest levels of performance. Exploring these areas may provide actionable insights for coaches aiming to sustain a competitive advantage in NCAA Women's College Basketball.

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Appendix A

Literature Search Terms

Search Term	Number of *SPORTDiscus* results	Number of *Google Scholar* results	Sources Screened to Include in Review
"women's basketball" and winning statistics	1	1	Gómez et al. (2009)
"key performance indicators" and "women's basketball"	1	56	Leicht et al. (2017)
"binary logistic regression" and "women's basketball"	1	47	Gómez et al. (2013), Leicht et al. (2017)
binary logistic regression and women's basketball	4	~18,000	Gómez et al. (2013), Leicht et al. (2017)
"key performance indicators in basketball"	4	~89,400	Plakias et al. (2024), Tomanek et al. (2025), Zhou et al. (2024)
"binary logistic regression" and "key performance indicators"	9	~879	Leicht et al. (2017), Santos et al. (2020), Tomanek et al. (2025)
"binary logistic regression" and "key performance indicators" in sports	9	~218	Gifford and Bayrak (2023), Leicht et al. (2017), Tomanek et al. (2025)
performance analytics in women's basketball	N/A	~20,400	Sarlis and Tjortjis (2020)
box score metrics in basketball	N/A	~31,800	Zuccolotto et al. (2021)

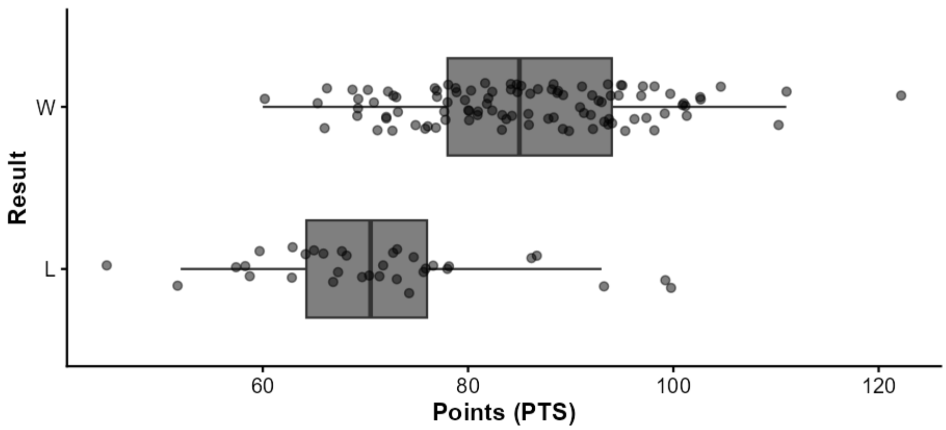
Note. Detailed search terms and corresponding database results in the literature search process.

Appendix B

Supplementary Figures

Figure B1

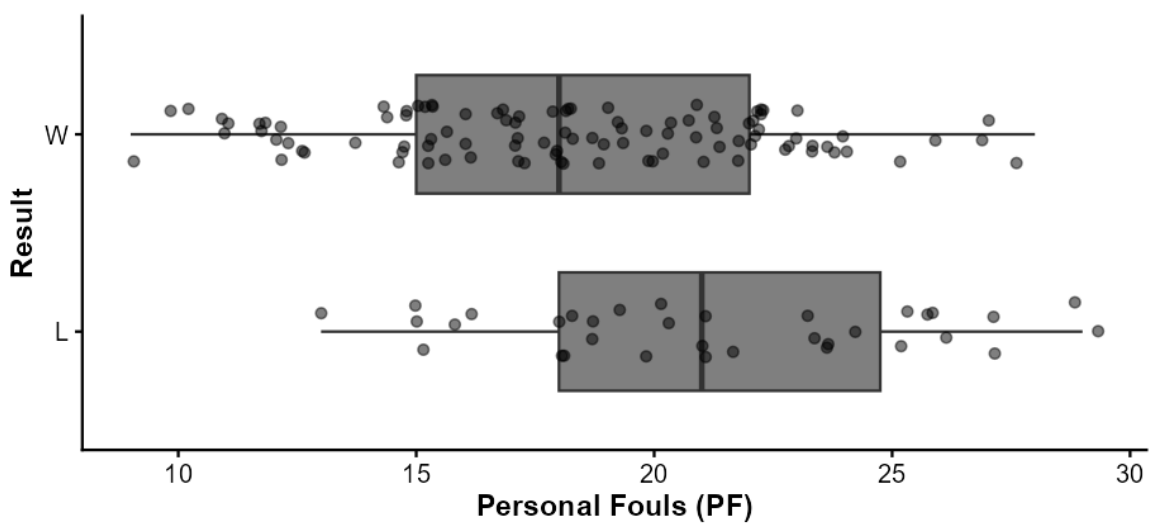
Points x Result (Team of Interest)



Note. Distribution of points in wins (W) versus losses (L) for the team of interest.

Figure B2

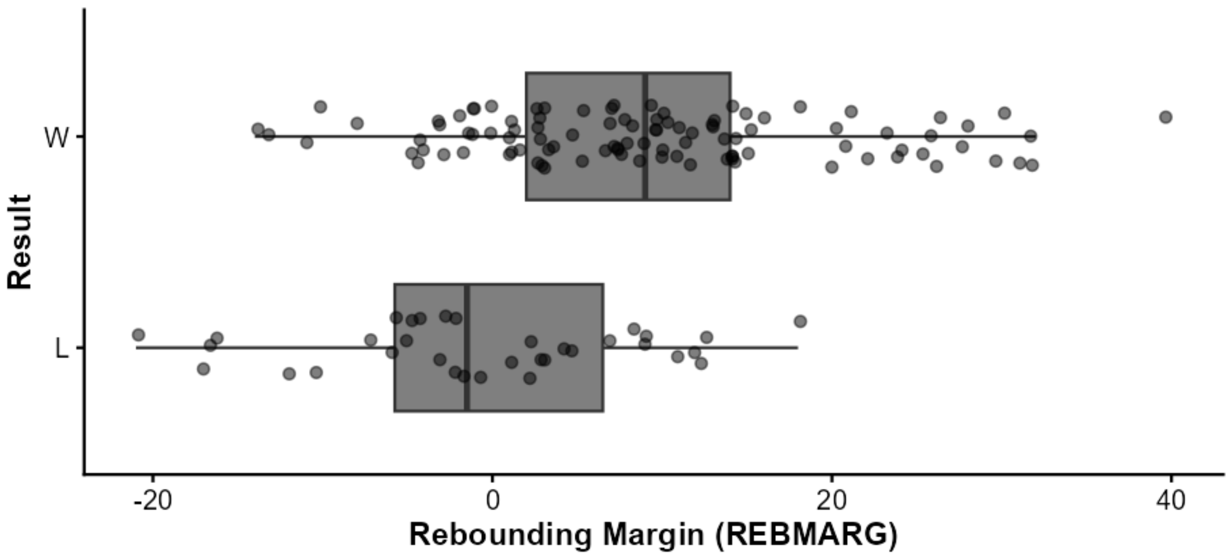
Personal Fouls x Result (Team of Interest)



Note. Distribution of personal fouls in wins (W) versus losses (L) for the team of interest.

Figure B3

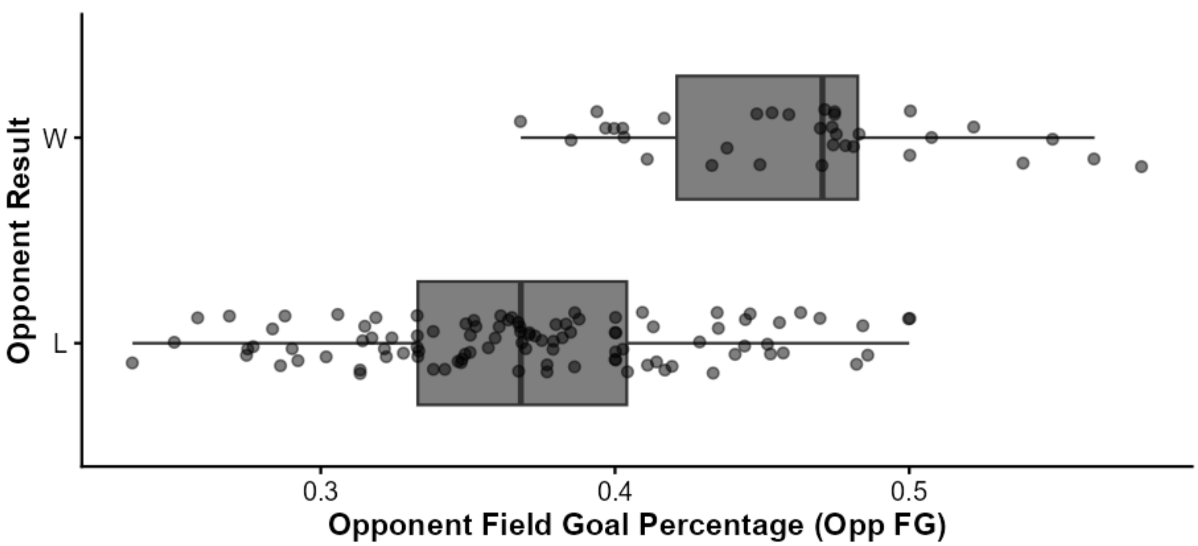
Rebounding Margin x Result (Team of Interest)



Note. Distribution of rebounding margin in wins (W) versus losses (L) for the team of interest.

Figure B4

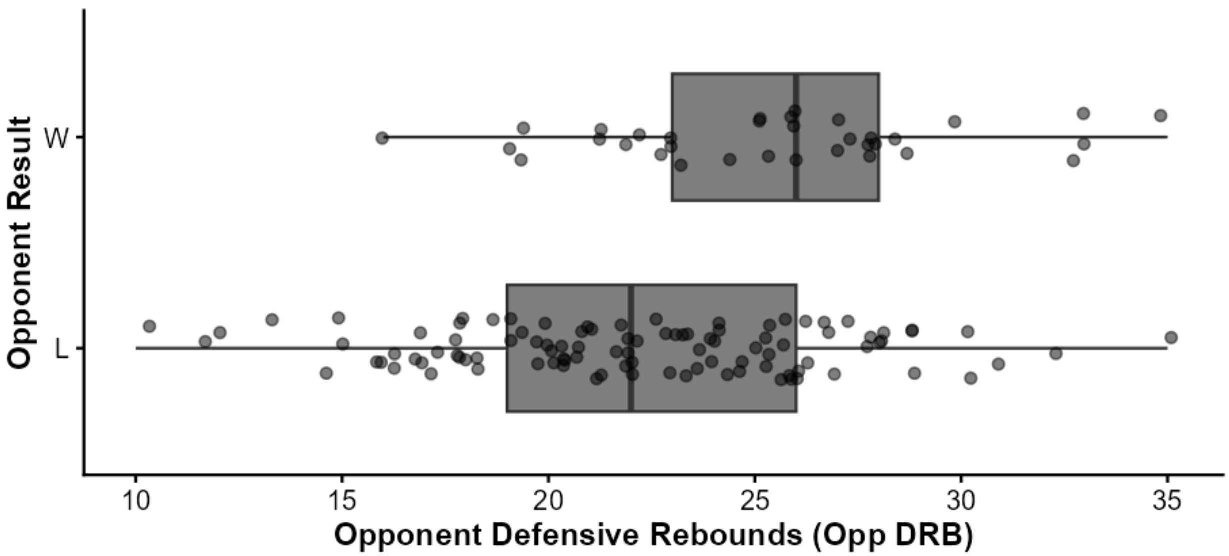
Opponent Field Goal Percentage x Result (Team of Interest)



Note. Distribution of opponent field goal percentage in opponent wins (W) versus losses (L) in games versus the team of interest.

Figure B5

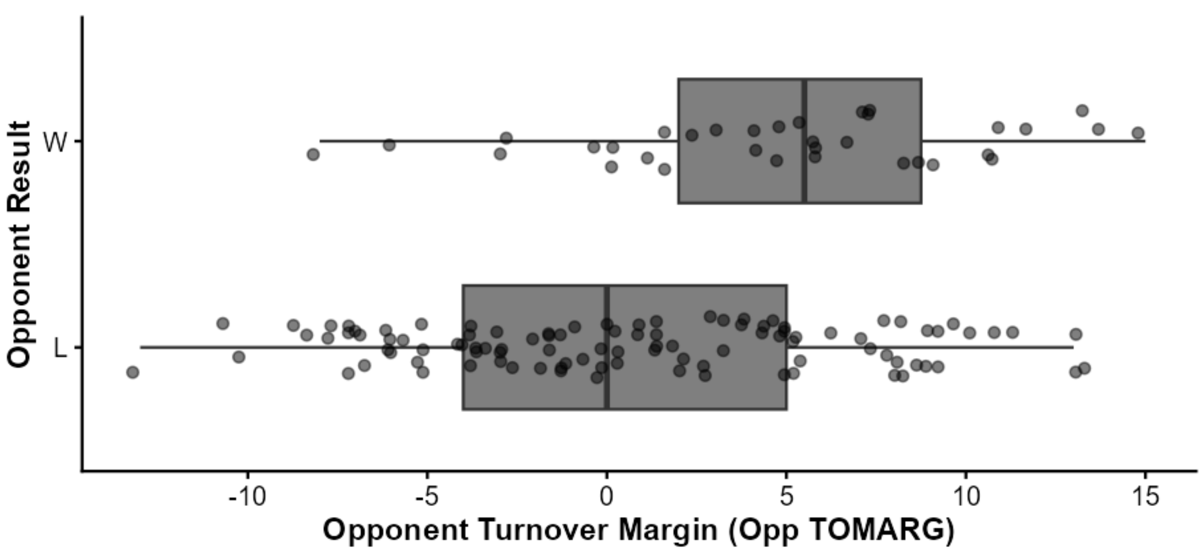
Opponent Defensive Rebounds x Result (Team of Interest)



Note. Distribution of opponent defensive rebounds in opponent wins (W) versus losses (L) in games versus the team of interest.

Figure B6

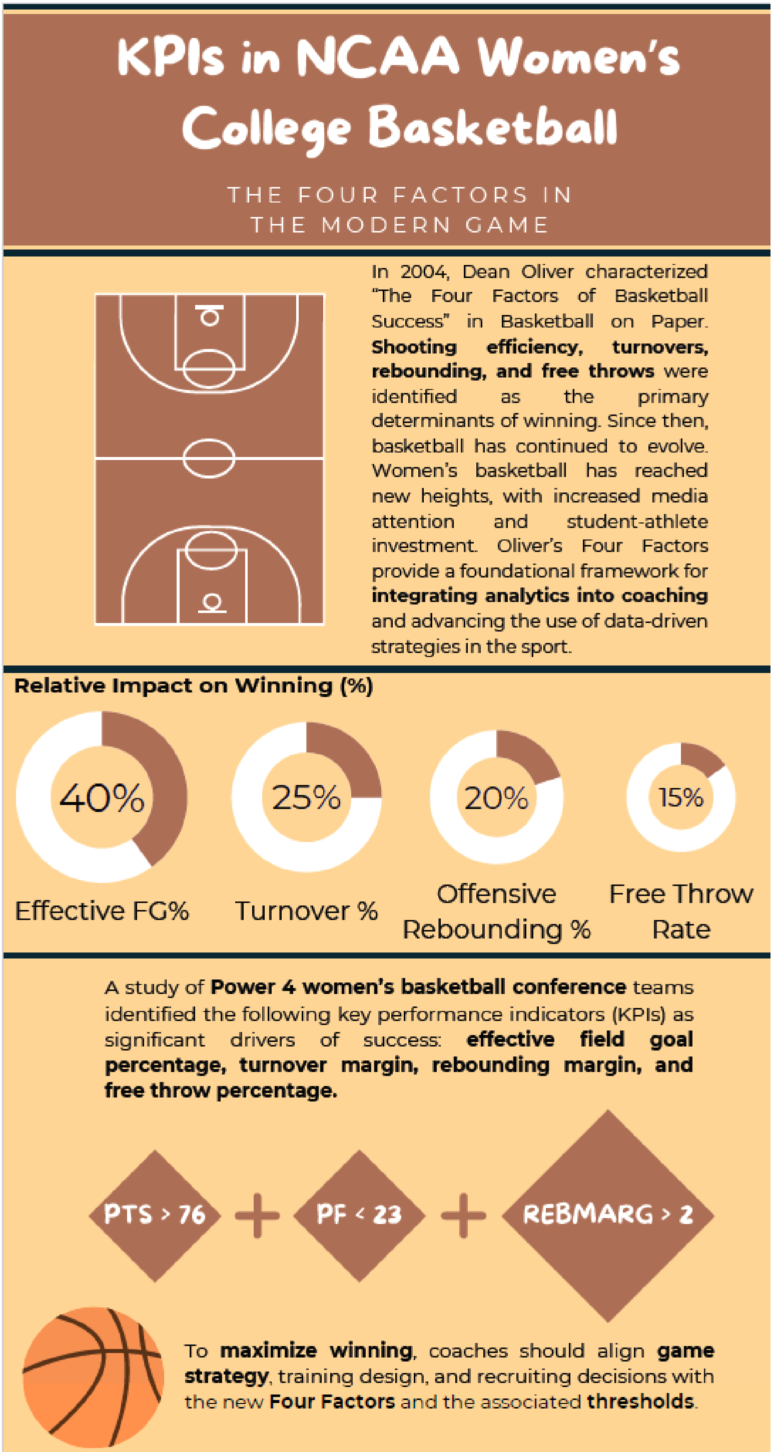
Opponent Turnover Margin x Result (Team of Interest)



Note. Distribution of opponent turnover margin in opponent wins (W) versus losses (L) in games versus the team of interest.

Figure B7

KPIs Infographic



Note. The infographic depicts Oliver's Four Factors, the study's identified KPIs and statistical thresholds, and the importance of integrating analytics into basketball coaching. Adapted from a template in Canva.