Social Media in Basketball: Measuring NBA Team Performance and Fan Twitter Sentiment to Gauge Fan Engagement and Revenue Generation

MATTHEW KWAN

Abstract

Basketball has evolved and is continuing to evolve in parallel with media and communication. The 21st century bears witness to the digitization of basketball, media, and communication with the advent of social media. Arguably the most esteemed professional basketball league in the world, the National Basketball Association (NBA) observes fans and players alike conversing about the game through social media platforms available across the world. One of the most popular platforms, Twitter, enables anyone with a computer to write a textual post known as a “tweet” that can be made viewable to the public. The Twitter landscape holds a trove of data and information including “sentiment” for NBA teams to analyze with the goal of improving the success of their team from a managerial perspective. Two aspects this paper will examine are fan engagement and revenue generation from the perspective of several franchises in the NBA. The purpose of this research is to explore and discover if key measures of performance including both the number of points scored in a game and the game outcome either being a win or a loss, and the location of a game being won either at home or away on the road influence fan Twitter sentiment and if there is a correlation between fan Twitter sentiment and game attendance. The statistical computing tool RStudio in combination with data compiled from online databases and websites including Basketball Reference, Wikipedia, ESPN, and Statista are employed to execute two t-tests, two analysis of variance (ANOVA) tests, and one correlation test. The results indicate there is a significant difference in fan Twitter sentiment between high-scoring games and low-scoring games, between game wins and losses, among games being won at home versus away on the road, and there is no conclusion that can be made regarding any existing correlation between fan Twitter sentiment and game attendance.

Table of Contents

List of Figures

List of Tables

INTRODUCTION & BACKGROUND INFORMATION

NBA franchises use social media platforms such as Twitter to engage with fans where each team has their own official Twitter account. The Charlotte Hornets are one example of a team that has a fan base and Twitter following exceeding one million users (Charlotte Hornets, n.d.). The Hornets' fan base strives to ingrain the team they support into their own identity, showing how they are engaged at the highest level. According to an article from the journal Sport Marketing Quarterly in reference to the Charlotte Bobcats returning to its original name, the Charlotte Hornets, "…the city's passion for the original Hornets, and subsequent active pursuit to return the name to the organization, resulted in the creation of a new Hornets brand that produced increased levels of support from its fan base and revenue generating opportunities," (Wear et al., 2018). The Charlotte Hornets are one example of how they were able to capitalize on gains in both fan engagement and revenue generation by rebranding to their original name. The rebranding's success can be measured by noticing how the Hornets were able to achieve new heights that were not achieved in the last season while playing under the Charlotte Bobcats' name. For example, the team rose from being ranked 25th in the NBA for game attendance to being ranked 19th and experienced a 300% increase in merchandising sales, while winning fewer games than during the previous season (Wear et. al, 2018).

In the current age of social media, searching for ways to boost fan engagement and revenue generation is not as straightforward as rebranding the name of a team. To deliver on demands that require franchises to strive to improve fan engagement and revenue generation, data analytics has captivated sports leagues across the world including the NBA. According to an article from the International Journal of Advanced Research in Computer Science, "data analysis is the process of applying organized and systematic statistical techniques to describe, recap, check, and condense data…" (Mishra et. al, 2017). Before teams can draw insights from social media data using data analysis, they need to mine the data using methods such as data and text mining. Once teams can accrue the data after having mined it, they need to clean the data so it can be processed using analytical tools and statistical tests. From the perspective of social media data, one key measurement regarding the textual element of social media is sentiment, which is the positive, negative, or neutral emotion behind text. Sentiment enables franchises to catch a glimpse of what a fan may be feeling in their customer experience with the franchise as a small to medium-sized business. One can explore if a franchise's fan experience team performed well and succeeded in creating a fan for life. To measure this, the fan experience team can observe the purchasing behavior of a team's fans over time in relation to their customer life cycle. According to an article from the Journal of Interactive Marketing, the customer life cycle shows "older customers with a long history of transactions…are more likely to be retained and hence have a longer life cycle as compared to newly acquired younger customers," (Jain & Singh, 2002). By studying Twitter behavior in combination with purchasing behavior, the fan experience team can learn about the emotion and feeling behind fans' purchasing behavior. For example, if a fan is seen consistently writing tweets about the team and wearing merchandise in photos posted on Twitter game after game, this may be a fan created for life. This is an applicable scenario that can be further explored by analyzing the sentiment of fans' tweets and textual data in a process known as "sentiment analysis."

The social media platform Twitter is a prime source of the textual data that enables NBA franchises to conduct sentiment analysis in studying fan behavior found in online discussion of the NBA. A team may be able to perform better than its competitors by running its social media platform to attract the greatest number of loyal fans possible. However, teams cannot accomplish this through social media alone as they require additional measures of success that depend on the team's performance on the court. These measures include the level of offense produced from scoring output and the game outcome categorized from either winning or losing. According to *The Elusive Fan* by Irving Rein, Philip Kotler, and Ben Shields, the authors state it is "…essential that the majority of sports products brand their attributes independent of competitive outcomes…Anna Kournikova, Vince Carter, and Bob Uecker have succeeded without much winning and have built their brands on other attributes such as looks, slam dunks, and quirky broadcasting," (Rein et. al, 2006). Here *The Elusive Fan* notes how teams and their fan base should stray away from relying on team performance alone to determine the health of a franchise. Instead, franchises should be equally reliant on both team performance and their ability to market the franchise in building a strong connection with their fans like the Charlotte Bobcats' rebranding. This is not to say that scoring output and game outcome lack importance, but rather franchises need to continue recognizing that a winning franchise and culture is built upon more than team performance metrics alone.

If a team starts to win consistently, more fans may follow and support that team, just as if a team starts to lose more games than win games, less fans may follow and support that team. This idea supports Robert Cialdini's research on the phenomena of "BIRGing" and "CORFing" which stand for "basking in reflected glory" and "cutting off reflected failure," respectively (Jensen et. al, 2016). Both "BIRGing" and "CORFing" not only happen at the professional level of sports, but also happen at the collegiate level. Cialdini's original study in 1976 observed a group of college football fans being "more than twice as likely to wear school-affiliated apparel after wins and 55% less likely after losses," (Jensen et. al, 2016). This study showed fans partaking in physical "BIRGing" and "CORFing" by having a choice of team apparel to wear.

However today, fans can now partake in digital “BIRGing” and “CORFing” through having a choice of which professional or collegiate team to follow and post about on social media. Social media guides franchises in allowing them to pinpoint when digital “BIRGing” and “CORFing” may be happening within their online fan base by being able to study fan activity including online discussion on platforms like Twitter.

Some teams including the New York Knicks have had a loyal fan base since the teams’ creation, where if either the team is performing well or poorly, the fan base continues to provide its loyal support. From the viewpoint of social media, the New York Knicks have succeeded in maintaining a fan base above 1 million Twitter users and above 5 million Facebook users since September 2014 (see Appendix D). Teams like the New York Knicks are given the opportunity to enhance fan engagement and revenue generation through their ability to leverage and serve their loyal social media following. This can be accomplished from running marketing campaigns to posting content such as short lighthearted videos featuring players answering random trivia questions to engage fans. Other teams are not as fortunate by being pressured to focus more on improving team performance and cohesion or else risk suffering a hit to their fan base. For example, a younger franchise, the New Orleans Pelicans ranked second to last in franchise value in 2021 (see Appendix E) and continues to receive flak for the controversy that ensued over the past few years regarding players like Anthony Davis and Zion Williamson. The fans who decide to jump from team to team may be regarded as “bandwagon fans,” where they possess some of the most valuable sentiment and textual data that can be tracked cumulatively for a given team. The high value of their sentiment and textual data comes from their ability to constantly pay attention to which teams are performing the best and are worth supporting.

Beginning with a team’s level of offense and wins versus losses, the potential exists for these performance metrics to impact fan Twitter sentiment. Once there is an observable impact on fan Twitter sentiment, the potential to improve fan engagement and revenue generation exists from being able to apply what was learned from studying any change in fan Twitter sentiment. This thesis project is first testing for the impact of a team’s performance measured through offensive prowess and wins versus losses on fan Twitter sentiment. Next, the thesis project is testing for the impact of a team winning at home versus away on the road on fan Twitter sentiment. The thesis project’s testing phase concludes with testing to see if any correlation exists between fan Twitter sentiment and game attendance. The project attempts to track cumulative tweets and their sentiment for the following teams across thirty games per team for a total of one hundred and twenty games: the Phoenix Suns, Los Angeles Lakers, New Orleans Pelicans, and New York Knicks. This thesis intends to build upon existing concepts of NBA fan engagement and revenue generation with the goal of supporting current research done on social media and marketing data analytics in the context of professional basketball played in the National Basketball Association.

LITERATURE REVIEW

Fan engagement and revenue generation are two key areas of performance that enable franchises to innovate and think outside the box with the goal of improving each area. For example, the NBA itself had undergone a change to the format of the championship seven-game series, the NBA Finals. According to an article from the Eastern Economic Journal, the NBA altered the championship format from a 2-2-1-1-1 series to a 2-3-2 series format, causing an increase in the tournament length, while reducing the inconvenience of travel (Caudill & Mixon, 1998). As a result of this format change, the league granted itself the ability to boost ratings and television revenue. The league accomplished this by increasing the probability of the series lasting longer by ending in a game six while reducing the probability of the series ending in a shorter span of five games (Caudill & Mixon, 1998).

Beyond changing the format of the NBA Finals championship series, the NBA is now confronted with the opportunity to enhance fan engagement and revenue generation by making effective use of social media. Ever since the beginning of social media platforms like Twitter, sports teams have been tasked with devising new ways of developing fan attraction through social media. According to an article from the journal Sport Marketing Quarterly, Facebook enables a sports team to increase fan engagement by allowing them to present their Facebook page as “official” in addition to allowing fans to engage with the page in a two-way dialogue format (Pronschinske et. al, 2012). By allowing teams to indicate to fans that they were visiting the official page of those sports teams, Facebook enabled teams and fans to build a level of trust vital to fan engagement and revenue generation. Facebook provided a platform for both the teams and fans to communicate in a memorable way, leaving a positive and tangible experience for the fans to take away.

The valuable interactions that occur between a sports organization and its fans on social media exist in other major sports leagues too including the Major League Baseball (MLB) organization. According to an article on a study regarding MLB team-fan interactions on social media by Derek D. Reed from the journal Behavior Analysis: Research and Practice, “Twitter fan growth accelerates hyperbolically as a function of Twitter MLB team-fan interactions” (Reed, 2016). From seeing how social media has built a sense of connection between fans and teams in the MLB, the NBA is in a similar situation given the level of social media interaction already happening between NBA teams and their fans. Reed states how “social media has emerged as a new avenue in which fans can interact directly—via Tweets (and Retweets), favorites, shares, follows, and so forth—with their favorite team or athlete, regardless of the impersonal or anonymous nature of such interactions," (Reed, 2016). The mention of "athlete" in addition to "team" indicates how certain sports fans especially in the NBA tend to follow a team only if their favorite player is playing for that team. By revisiting the idea of "bandwagon fans," a fan who leaves one team to follow a new team in order to support their favorite player joining that new team can be considered as another type of "bandwagon fan." What separates these fans from the original "bandwagon fans" is noticing how these fans are attaching the face of an athlete to the team they are supporting. Once a sports organization realizes when their fans may be prioritizing an athlete's success over the team's success, the sports organization may encourage their player to become more active and visible on the team's social media platforms. By having the player appear more often on the team's social media platforms, the fans may begin to reconnect the team to their favorite player instead of separating the two from each other. This connection ensures the fan does not limit their engagement to an individual player on the team, but rather shares their engagement with the entire team in showing support for the entire franchise.

Maximizing the performance of the team and its players during a game may be viewed as an optimal route to improving fan engagement and revenue generation. According to an article from the Journal of Applied Sport Management, "in a practical sense, an NBA team may strongly consider promoting the team's offensive prowess regardless of their defensive stature in the league to attract fans to their games," (Davis & Miller, 2019). The more offensive a team's playstyle tends to be, the more memorable and captivating that team may be in the eyes of the average or potential fan watching that team play. A way offense can be measured is through the scoring output produced by a team playing against another team. A high-scoring output may indicate a team was playing with more offense and less defense while a low-scoring output may indicate a team was playing with less offense and more defense.

Regardless of the number of points being scored in a game by one team, certain fans may be more focused on the types of plays that are being made by the players to achieve those points. Certain players like Stephen Curry embrace shooting “lights out” at a great distance beyond the three-point line. Other players like Anthony Edwards choose to show off their gifted athleticism by striving for ambitious dunks and “posters”. Playstyles like these may be credited to the offensive playstyle the entire team culture may be imparting onto its players. Contrarily, instead of one team’s culture impacting the playstyle of one player, there could be an individual player or role model on the team influencing the way the entire team plays. With every play that is witnessed, with every point that is scored, fans in the arena are witnessing these events take place and are developing their own sentiment-based reactions in real time. Some fans express their sentiment online by writing and posting tweets that are available to be read by the public and analyzed by NBA sports organizations.

HYPOTHESIS DESIGN

1. Hypothesis I: Playing with more offensive prowess measured from having a high-scoring game will increase Twitter fan sentiment versus having a low-scoring game.
2. Hypothesis II: Achieving game victory measured from accruing game wins will increase Twitter fan sentiment versus accruing game losses.

3. Hypothesis III: The effect of a team winning at home versus away on the road during the regular season on Twitter fan sentiment will differ between these two locations where a game is won.
4. Hypothesis IV: There will be a positive correlation between Twitter fan sentiment and game attendance.

RESEARCH DESIGN

I. Methodology

All research problems regarding the hypotheses listed above required the use of version 2 of the Twitter API in combination with the R programming language. Team selection for each of the hypotheses included the following: the **2020-21 Phoenix Suns – Hypothesis I**, the **2020-21 Los Angeles Lakers – Hypothesis II**, the **2019-20 New Orleans Pelicans – Hypothesis III**, and the **2018-19 New York Knicks – Hypothesis IV**. Hypothesis I observed the fifteen games containing the greatest number of points scored by the Phoenix Suns and the fifteen games containing the least number of points scored by the Phoenix Suns in the 2020-21 regular season, totaling 30 games being observed. Hypothesis II observed 15 randomly sampled games resulting in a win for the Los Angeles Lakers and another 15 randomly sampled games resulting in a loss for the Los Angeles Lakers in the 2020-21 regular season, totaling 30 games being observed. The games in the second hypothesis were accumulated by using R’s “sample()” function in RStudio. Hypothesis III observed the New Orleans Pelicans’ fifteen games won at home and their fifteen games won away on the road in the 2019-20 regular season, totaling 30 games being observed.

Hypothesis IV observed the first 30 home games of the New York Knicks in the 2018-19 regular season.

For every game observed in this thesis, 1,000 tweets were randomly sampled from the calendar day of each game in the time frame from 12:00am to 11:59pm, for a total of 120,000 tweets being pulled across 120 games. For the first two hypotheses, the teams were chosen based on personal preference as the author of this thesis is a huge supporter of both the Los Angeles Lakers and the Phoenix Suns. For Hypothesis III, the New Orleans Pelicans were chosen because a team with exactly thirty wins being equally distributed between home and away games in one season was needed for the ANOVA tests being run. The New Orleans Pelicans satisfied this requirement by achieving a total of thirty wins during the 2019-20 season with fifteen being won at home and the other fifteen being won away on the road. For Hypothesis IV, the New York Knicks were chosen because the author chose to examine the team with arguably the worst record and performance in the 2018-19 season, the final season shortly before the COVID-19 pandemic began in the upcoming 2019-20 season. The first two hypotheses both included games from the 2020-21 season because the author viewed this season as being one of the most discussed seasons in NBA history from an online social media standpoint. The author made this decision due to seeing how all thirty NBA arenas were required to limit attendance capacity as a result of the pandemic, showing how many fans were required to watch their team's games from home. By causing fans to stay home instead of allowing them to watch the game live at the arena, some fans may have had their own mobile device nearby while watching a game on television instead of inside an arena. Fans had a higher likelihood of being distracted by their mobile devices while watching NBA games at home, a situation that gave way to a higher likelihood of fans expressing their sentiment through posts made on social media platforms including Twitter.

II. Data Collection

To establish the connection between RStudio and version 2 of the Twitter API, the "academictwitteR" library in R was used to access the full functionality of the API after access was properly authorized using the bearer token provided by the thesis director, Professor Daniel McIntosh. The sentiment of every tweet involved in this project was captured using the 'sentimentr' library in R and stored and added as a new vector to the original data frame containing the tweets. Every piece of textual data from every tweet was cleaned for sentiment analysis by running the "gsub()" function in addition to the "tolower()" function across five lines of code per game.

The data collection in Hypothesis I first encompassed pulling down 30,000 randomly sampled tweets across 30 different games involving the Phoenix Suns in the 2020-21 season. The methodology for mining these tweets involved passing in a search string where the search string used was "suns." Any tweet involving the word "suns" within the set time frame would have an opportunity to be pulled down into a data frame containing that tweet and additional metadata. The 30,000 tweets were then divided into their own 1,000-tweet samples with one sample pertaining to one of thirty games. Additionally, data pertaining to the final scores of all 30 games was examined by accessing Basketball Reference (basketball-reference.com) in order to locate which games were the 15 highest-scoring games versus the 15 lowest-scoring games by the Phoenix Suns of the 2020-21 season. The scores themselves did not go into the actual analysis and were only used to identify the games which required Twitter text mining to be performed. Two final data frames were created with one merging all 15,000 tweets pertaining to high-scoring games and the other merging all 15,000 tweets pertaining to low-scoring games.

The data collection in Hypothesis II first encompassed pulling down 30,000 randomly sampled tweets across 30 different games involving the Los Angeles Lakers in the 2020-21 season. The methodology for mining these tweets involved passing in a search string where the search string used was “lakers.” Any tweet involving the word “lakers” within the set time frame would have an opportunity to be pulled down into a data frame containing that tweet and additional metadata. The 30,000 tweets were then divided into their own 1,000-tweet samples with one sample pertaining to one of thirty games. Additionally, data pertaining to the final outcome of each game was examined by accessing Basketball Reference (basketball-reference.com) in order to locate which games resulted in a win versus a loss for the Los Angeles Lakers in the 2020-21 season. The game outcomes themselves did not go into the actual analysis and were only used to identify the games which required Twitter text mining to be performed. Two final data frames were created with one merging all 15,000 tweets pertaining to game wins and the other merging all 15,000 tweets pertaining to games losses.

The data collection in Hypothesis III first encompassed pulling down 30,000 randomly sampled tweets across 30 different games each involving the New Orleans Pelicans winning the game either at home or away on the road during the 2019-20 season. The methodology for mining these tweets involved passing in a search string containing the user mention of the New Orleans Pelicans' official Twitter account username where the search string used was "@PelicansNBA" (see Appendix G). Any tweet involving the user mention of the New Orleans Pelicans' Twitter account within the set time frame would have an opportunity to be pulled down into a data frame containing that tweet and additional metadata. The 30,000 tweets were then divided into their own 1,000-tweet samples with one sample pertaining to one of thirty games. Additionally, data pulled from Wikipedia (en.wikipedia.org) pertaining to the three-letter abbreviations of each of the New Orleans Pelicans' opponents was used in the actual analysis in order to identify which team lost to the Pelicans at which location relative to the Pelicans. The two groups being compared and contrasted with each other in Hypothesis III are the collection of fifteen games won at home and the collection of fifteen games won away on the road. Two final data frames were created with the first data frame merging all 30,000 tweets with each 1,000-tweet sample pertaining to one game out of thirty games. The second data frame combined two 1,000-tweet samples for a total of 2,000 tweets using one home win on February 11th, 2020 and one away win on December 23rd, 2019 with both games being won against the Portland Trailblazers. This data frame was made to draw insight on the basis of studying the New Orleans Pelicans on an individual game-versus-game level in the context of winning against the same team at home and away on the road.

The data collection in Hypothesis IV first encompassed pulling down 30,000 randomly sampled tweets across 30 different games involving the first 30 home games of the New York Knicks in the 2018-19 season. The methodology for mining these tweets involved passing in a search string where the search string used was "knicks." Any tweet involving the word "knicks" within the set time frame would have an opportunity to be pulled down into a data frame containing that tweet and additional metadata. The 30,000 tweets were then divided into their own 1,000-tweet samples with one sample pertaining to one of the first thirty home games of the New York Knicks' 2018-19 season. The mean sentiment of each game was calculated and stored inside of a variable that would be used to populate a vector containing the mean sentiment across all thirty games. Additionally, data pulled from ESPN (espn.com) pertaining to the game attendance of each game was used in the actual analysis in order to pair each game's mean sentiment value with the number of fans in attendance at that particular game being played at Madison Square Garden. One final data frame was created in order to pair the thirty mean sentiment values of each game alongside the thirty attendance numbers of each game.

III. Analysis

Each statistical analysis including the sentiment analysis piece was conducted using the R programming language in the integrated development environment RStudio. All visualizations regarding these analyses were created using the R programming language in the integrated development environment RStudio as well.

For Hypothesis I, a two-sample t-test was run using the function "t.test()." The two final data frames' "sentiment" vectors relating to the high-scoring games and the low-scoring games including the Phoenix Suns, the true value of the mean being 0, the alternative specifying a two-sided test, the confidence level of 95%, the value of "false" (F) both specifying the two variances are not treated as being equal and choosing to not run a paired t-test were all passed into the function. A box plot was created to visualize the results of this t-test.

For Hypothesis II, a two-sample t-test was run using the function “t.test().” The two final data frames’ “sentiment” vectors relating to the game wins and the game losses including the Los Angeles Lakers, the true value of the mean being 0, the alternative specifying a two-sided test, the confidence level of 95%, the value of “false” (F) both specifying the two variances are not treated as being equal and choosing to not run a paired t-test were all passed into the function. A box plot was created to visualize the results of this t-test.

For Hypothesis III, two one-way ANOVA tests were run using the function “aov()” and storing the results of running that function inside a variable representing the tabular model of the ANOVA. The “sentiment” vector in combination with the “game_id” vector that identified who was the opposing team that lost and the final data frame encompassing all thirty wins were all passed into the function. A box plot using the “plot_ly()” function was created to visualize the results of this ANOVA. For the remaining ANOVA, the methodology for running the ANOVA test was conducted in the same way as the first ANOVA; however, a final two-game data frame including the two wins against the Portland Trailblazers on February 11th, 2020 and December 23rd, 2019 instead of the final thirty-game data frame was passed into the function “aov().” A box plot using the “plot_ly()” function was created to visualize the results of this ANOVA too.

For Hypothesis IV, one correlation test was run using the “cor.test” function. The mean sentiment vector known as “game_mean_sentiment” and the vector “game_attendance” that housed the number of fans in attendance at a game were both passed into the function. One scatterplot and two line charts all using the “hchart()” function were created to visualize the results of the correlation test.

RESULTS

I. Hypothesis Test I

The first two sample t-test was run to compare average fan Twitter sentiment between the Phoenix Suns’ high-scoring games and low-scoring games during the 2020-21 season. There was a significant difference in mean sentiment between [high-scoring games] (M = [0.070], SD = [0.194]) and [low-scoring games] (M = [0.054], SD = [0.202]); t(29947) = [6.920], p = [0.000]. The independent variable is the level of scoring output either being high or low while the dependent variable is the mean sentiment. The following table shows the test results, data label, group name, standard deviation (SD), and number of observations which are the games (see Table 1):

Data	merge_hi_gms$sentiment	merge_lo_gms$sentiment
Groups	High-Scoring Games	Low-Scoring Games
Mean	0.070	0.054
SD	0.194	0.202
Observations	15	15
df	29947	
t	6.920	
p-value	0.000	
95% CI Upper	0.020	
95% CI Lower	0.011	

Table 1: Hypothesis Test I

The data consisted of two vectors being loaded into the test’s function in RStudio. The vector labeled “merge_hi_gms$sentiment” represents the column of sentiment values collected across all 15,000 tweets from the high-scoring games. The vector labeled “merge_lo_gms$sentiment” represents the column of sentiment values collected across all 15,000 tweets from the low-scoring games. By noticing how the mean sentiment of the high-scoring games is greater than the mean sentiment of the low-scoring games, the suggestion can be made that when the Phoenix Suns scored more points from one game to the next, the team and the organization itself received more positive feedback and reactions from their fans and other spectators communicating on Twitter. The following box plot visualizes the output (see Figure 1):

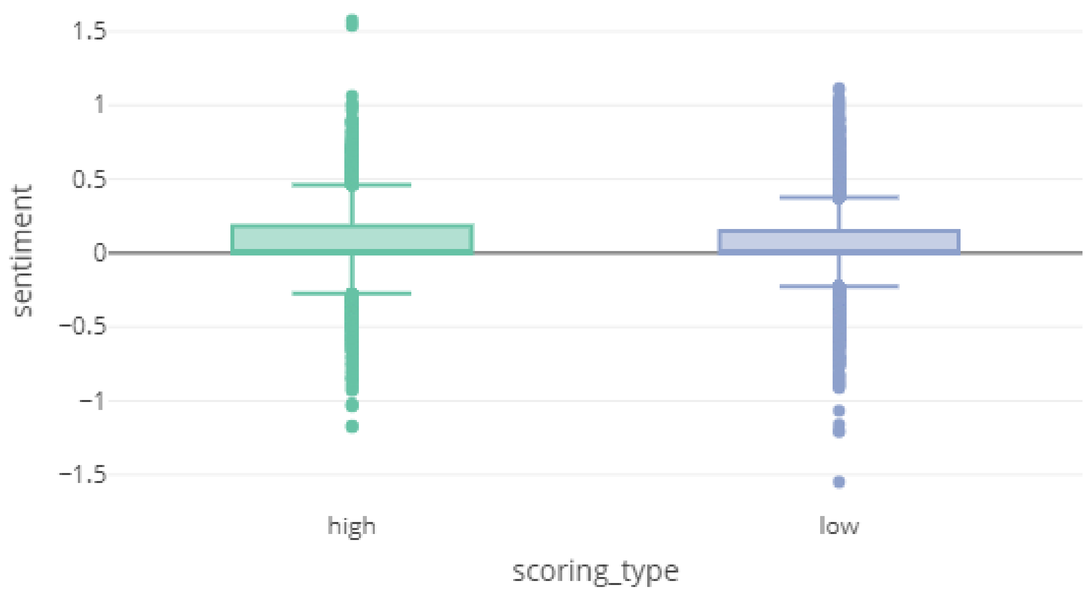


Figure 1: Hypothesis Test I Box Plot

The plot on the left labeled “high” represents the sentiment of games that had a high level of scoring and can classify their “scoring_type” as high. The plot on the right labeled “low” represents the sentiment of games that had a low level of scoring and can classify their “scoring_type” as low. The high-scoring games convey a higher level of sentiment being achieved in comparison with the low-scoring games that convey a lower level of sentiment being achieved. Additionally, the upper whisker of the plot pertaining to the high-scoring games is shifted slightly higher than the upper whisker pertaining to the low-scoring games, revealing a higher level of sentiment being expressed for the 2020-21 Phoenix Suns' high-scoring games.

A tweet by Matthew Warwick denoted by a highly positive sentiment value of approximately 1.574 in regard to the Suns' 32-point win over the Portland Trailblazers is shown below (see Figure 2):

Figure 2: Tweet by Matthew Warwick ([Screenshot of tweet by Matthew Warwick], 2021)

The managerial significance of this tweet is recognizing that this fan appears to support multiple Arizona sports teams through the Phoenix Suns and Arizona Coyotes. If the Phoenix Suns were to cater to more sports fans outside basketball such as hockey fans of the Arizona Coyotes, the Suns' fan base could experience growth improving fan engagement and revenue generation. This would allow the Suns to partner with the Coyotes in pushing out marketing campaigns and promotions geared towards bridging the fan bases between the two Arizona sports franchises.

A tweet by Wadeh Maroun denoted by a highly negative sentiment value of approximately -1.575 during the time frame of one of the Suns' lower-scoring games against the Charlotte Hornets is shown below (see Figure 3):

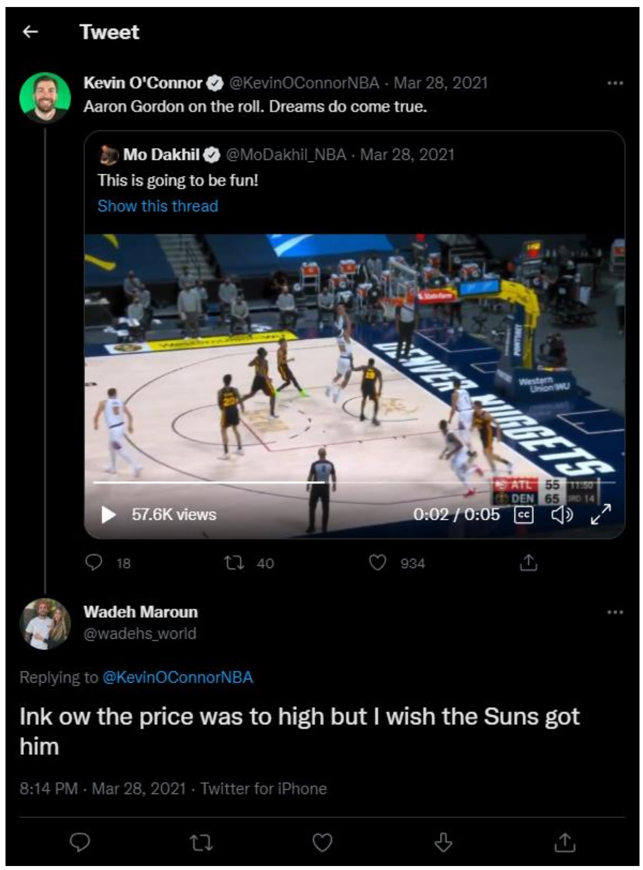


Figure 3: Tweet by Wadeh Maroun ([Screenshot of tweet by Wadeh Maroun], 2021)

The managerial significance of this tweet is recognizing that this fan appears to take an interest in potential players the Suns could trade for. Here the player being referenced is Aaron Gordon as shown in the highlight video thumbnail above the tweet being analyzed. There is a possibility this fan could be a fan of both Aaron Gordon and the Phoenix Suns. The Suns could impart a positive experience on this fan by giving them an opportunity to attend a Suns' game where Aaron Gordon and his team are visiting. This would allow the fan to enjoy watching both their favorite team and one of the visiting players they admire and believe would fit well playing for the Suns.

II. Hypothesis Test II

The second two sample t-test was run to compare average fan Twitter sentiment between the Los Angeles Lakers' game losses and game wins during the 2020-21 season. There was a significant difference in mean sentiment between [losses] (M = [0.023], SD = [0.184]) and [wins] (M = [0.039], SD = [0.165]); t(29653) = [-8.058], p = [0.000]. The independent variable is the competitive outcome of a game either being a loss or win while the dependent variable is the mean sentiment. The following table shows the test results, data label, group name, standard deviation (SD), and number of observations which are the games (see Table 2):

Data	merge_gms_l$sentiment	merge_gms_w$sentiment
Groups	Losses	Wins
Mean	0.023	0.039
SD	0.184	0.165
Observations	15	15
df	29653	
t	-8.058	
p-value	0.000	
95% CI Upper	-0.012	
95% CI Lower	-0.020	

Table 2: Hypothesis Test II

The data consisted of two vectors being loaded into the test's function. The vector labeled "merge_gms_l$sentiment" represents the column of sentiment values collected across all 15,000 tweets from the game losses. The vector labeled "merge_gms_w$sentiment" represents the column of sentiment values collected across all 15,000 tweets from the game wins. By noticing how the mean sentiment of the losses is less than the mean sentiment of the wins, the suggestion can be made that when the Los Angeles Lakers lost a game in relation to their previous game, the team and organization itself received more negative feedback and reactions from their fans and other spectators communicating on Twitter. The following box plot visualizes the output (see Figure 4):

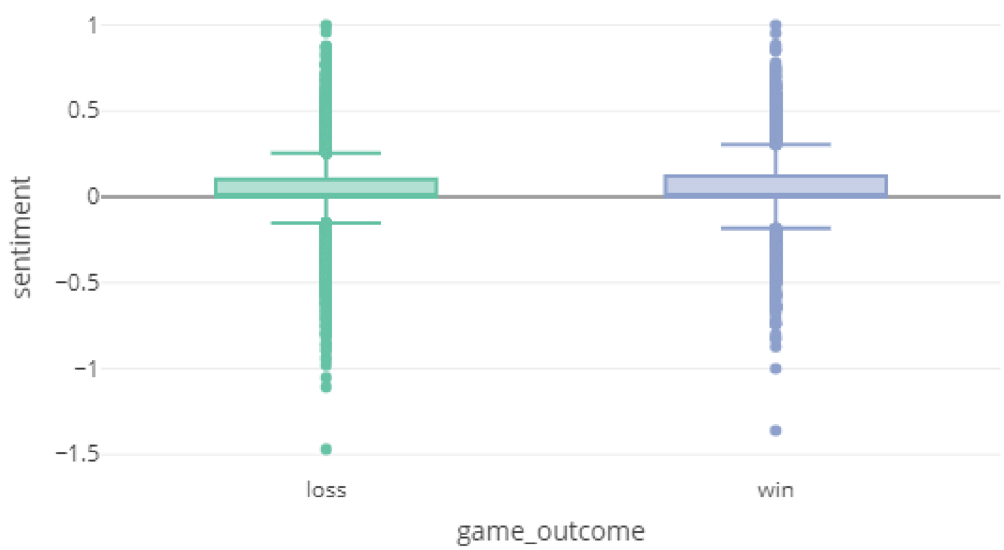


Figure 4: Hypothesis Test II Box Plot

The plot on the left labeled "loss" represents the sentiment of games that resulted in a Lakers' loss and can classify their "game_outcome" as a loss. The plot on the right labeled "win" represents the sentiment of games that resulted in a Lakers' win and can classify their "game_outcome" as a win. The game losses convey a lower level of sentiment being achieved in comparison with the game wins that convey a higher level of sentiment being achieved. Additionally, the upper whisker of the plot pertaining to the losses is shifted slightly lower than the upper whisker of the plot pertaining to the wins, revealing a lower level of sentiment being expressed for the games resulting in a loss for the Los Angeles Lakers in the 2020-21 season.

III. ANOVAs

The first one-way ANOVA was performed to compare the effect of the two possible locations—home versus away—where the New Orleans Pelicans won a game during the 2019-20 season on average fan Twitter sentiment. This one-way ANOVA revealed that there was a statistically significant difference in mean fan Twitter sentiment between at least two groups ($F(1, 29998) = [104.6]$, $p = 0.000$). Tukey's HSD Test for multiple comparisons found that the mean value of fan Twitter sentiment was significantly different between home game wins and away game wins (95% C.I. = [0.015, 0.022]). The independent variable is the location of where the game was won either at home or away on the road while the dependent variable is the mean sentiment. The following tables display the results of running the first ANOVA and its post-hoc test (see Table 3 and Table 4):

	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
location_id	1	2.7	2.668	104.6	0.000
Residuals	29998	765.5	0.026		

Table 3: First ANOVA Output

Comparison	diff	lwr	upr	p adj
home-away	0.019	0.015	0.022	0

Table 4: First ANOVA Post-Hoc Test Output

In Table 3, “location_id” represents the independent variable either consisting of “home” or “away” as shown under “Comparison” in Table 4, indicating whether the New Orleans Pelicans won a game at home or away on the road. The dependent variable is the mean fan Twitter sentiment recorded within the time frame of each game. The results of the first ANOVA can be visualized in the following box plot (see Figure 5):

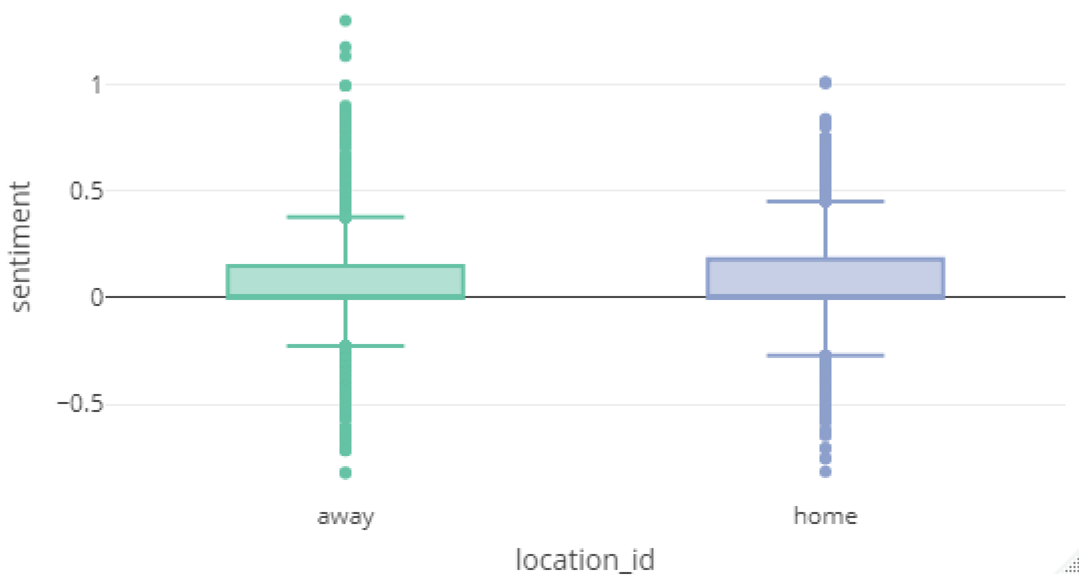


Figure 5: First ANOVA Box Plot

In Figure 5, the right box plot’s mean sentiment maximum value for the “home” wins is slightly greater than the left box plot’s mean sentiment maximum value for the “away” wins. However, the “away” wins appeared to yield outliers with mean sentiment values greater than outliers yielded by the “home” wins. In addition to noting how the mean sentiment expressed in relation to each of their thirty wins either being played at home or away on the road differed, the New Orleans Pelicans’ opponents differed as well. Basketball Reference reports the following nineteen opponents who each suffered at least one loss to the New Orleans Pelicans during the 2019-20 season: Boston Celtics, Chicago Bulls, Charlotte Hornets, Cleveland Cavaliers, Denver Nuggets, Detroit Pistons, Golden State Warriors, Houston Rockets, Indiana Pacers, Los Angeles Clippers, Memphis Grizzlies, Miami Heat, Minnesota Timberwolves, New York Knicks, Phoenix Suns, Portland Trailblazers, Sacramento Kings, Utah Jazz, and Washington Wizards. The New Orleans Pelicans saw the most success against the Portland Trailblazers by defeating them four times with two games being won at home and the remaining two being won on the road. The following box plot displays all thirty of the New Orleans Pelicans' wins during the 2019-20 season in relation to the average sentiment being expressed per game (see Figure 6):

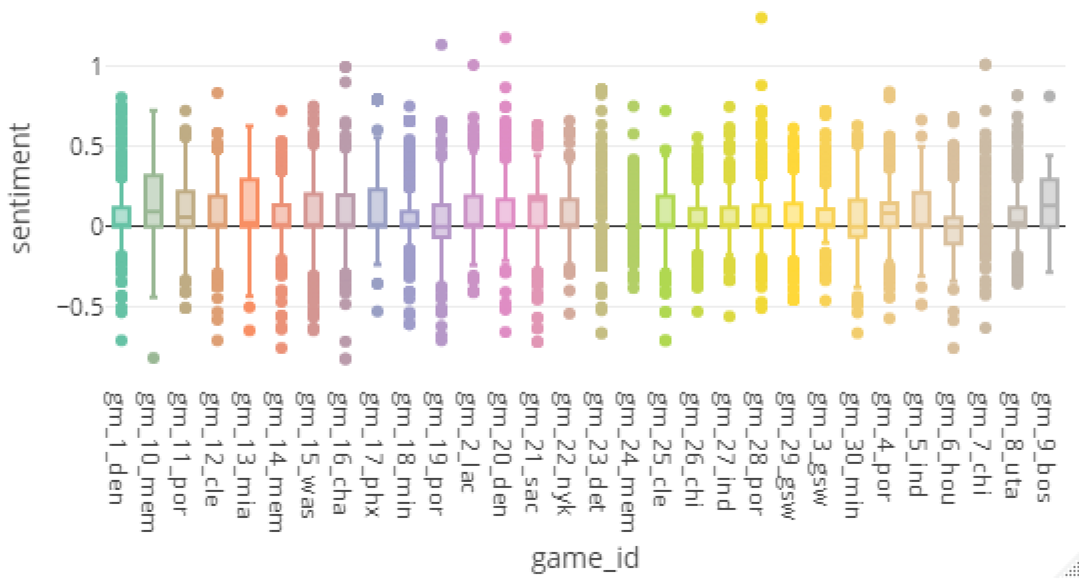


Figure 6: Box Plot of All Thirty Wins by 2019-20 NOP and Average Fan Twitter Sentiment

The results from the first ANOVA encompassing all thirty wins are similar to the second ANOVA involving both the home win against Portland on February 11th, 2020 and the away win against Portland on December 23rd, 2019. The second one-way ANOVA was performed to compare the effect of the two possible locations—home versus away—where the New Orleans Pelicans won a game during the 2019-20 season on average fan Twitter sentiment while playing against the Portland Trailblazers at two different games. This one-way ANOVA revealed that there was a statistically significant difference in mean fan Twitter sentiment between at least two groups ($F(1, 1998) = [128.4]$, $p = 0.000$). Tukey's HSD Test for multiple comparisons found that the mean value of fan Twitter sentiment was significantly different between winning at home and winning away on the road against the Portland Trailblazers (95% C.I. = [-0.097, -0.068]). The independent variable is the location of where the game was won against the Portland Trailblazers either at home or away on the road while the dependent variable is the mean sentiment per game. The following tables display the results of running the second ANOVA and its post-hoc test (see Table 5 and Table 6):

	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
game_id	1	3.4	3.396	128.4	0.000
Residuals	1998	52.86	0.026		

Table 5: Second ANOVA Output

Comparison	diff	lwr	upr	p adj
gm_19_por-gm_11_por	-0.082	-0.097	-0.068	0

Table 6: Second ANOVA Post-Hoc Test Output

In Table 5, "game_id" represents the independent variable either consisting of the away game "gm_19_por" or the home game "gm_11_por" as shown under "Comparison" in Table 6. Both games were won against the Portland Trailblazers during the 2019-20 season. The dependent variable is the mean fan Twitter sentiment recorded within the time frame of each game. The following box plot (see Figure 7) brings light to the fact that the New Orleans Pelicans were able to achieve a higher average sentiment after winning against the Portland Trailblazers at home in comparison with being away on the road. The label “game_id” consists of two parts: the game number out of the thirty games being analyzed in the test and the abbreviation of the losing team. For example, “gm_12_cle” translates to game twelve out of thirty being analyzed where the losing team was the Cleveland Cavaliers. Games one through fifteen were played at home while games sixteen through thirty were played away on the road. Sentiment is on the y-axis while “game_id” is on the x-axis (see Figure 7):

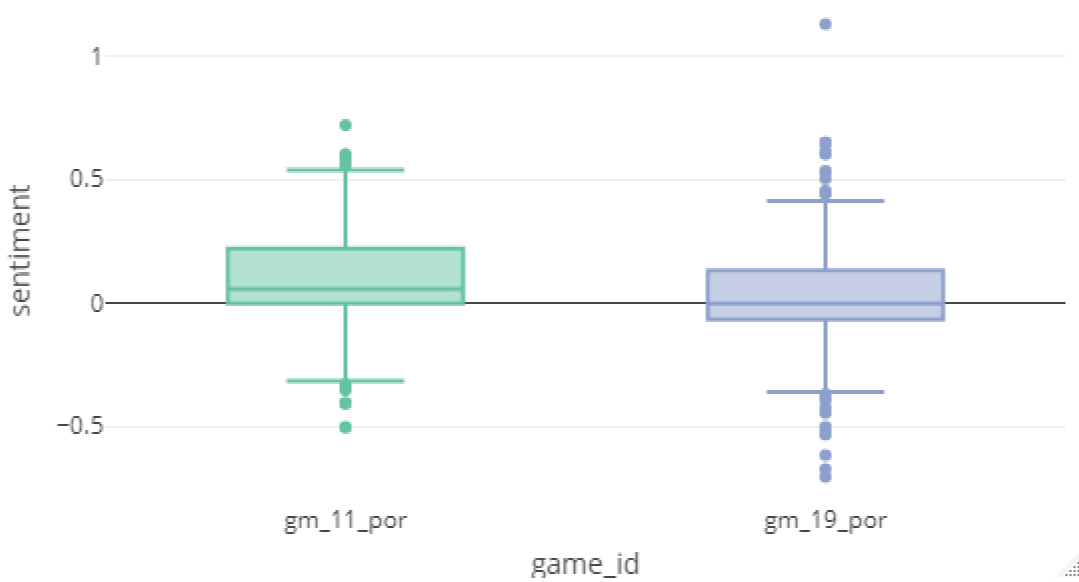


Figure 7: Second ANOVA Box Plot

The box plot on the left is labeled “gm_11_por” where “gm_11” indicates that this is the eleventh game out of all thirty games collectively being analyzed in the ANOVAs section of the project. The box plot on the right is labeled "gm_19_por" where "gm_19" indicates that this is the nineteenth game out of all thirty games collectively being analyzed in the ANOVAs section of the project. Based on the plot from winning at home in "gm_11_por," the Pelicans were able to break the 0.5-sentiment value threshold as evidenced by the left box plot's mean sentiment maximum value, but they came short of achieving that feat from winning on the road in "gm_19_por." One should note the New Orleans Pelicans won the away game two days before Christmas Day on December 23rd, 2019. This key detail that is not immediately captured from the sentiment analysis and box plot itself, may suggest the fans at the away game may have been in a less positive mood coming into the game happening shortly before Christmas. The added stress of having to prepare for the holidays beginning with Christmas may have caused fans to express lower sentiment in relation to the away game. On the contrary, Pelicans' fans at the away game may have been in a less positive mood by not being able to see and enjoy their team win at home instead of on the road while being this close to Christmas day. Looking beyond the time frame these games occur in allows for increased storytelling by examining factors and details not initially apparent from the data being analyzed.

IV. Correlation Test

A Pearson product-moment correlation coefficient was computed to assess any existing linear relationship between mean fan Twitter sentiment and game attendance of the New York Knicks' home basketball games at Madison Square Garden. There was neither a negative nor positive correlation that could be concluded to exist between the two variables, $r(28) = [-0.16]$, $p = [0.392]$. The *r* statistic was originally rounded to three decimal places as shown in Table 7. The independent variable is the average sentiment while the dependent variable is the game attendance. The table below shows the test results, data label, variable name, and number of observations which are the average sentiment values and attendance numbers (see Table 7):

Data	cor_df$game_mean_sentiment	cor_df$game_attendance
Variables	Game Average Sentiment	Game Attendance
CC	-0.162	
Observations	30	30
df	28	
t	-0.870	
p-value	0.392	
95% CI Upper	0.210	
95% CI Lower	-0.494	

Table 7: Correlation Test

The vector labeled "cor_df$game_mean_sentiment" represents the column of mean sentiment values collected across 30,000 tweets spanning all thirty games for the independent variable. The vector labeled "cor_df$game_attendance" represents the column of attendance numbers collected across all thirty games for the dependent variable. The New York Knicks played against twenty-three different teams during their first thirty games at Madison Square Garden. The twenty-three different teams include the following: Atlanta Hawks, Boston Celtics, Brooklyn Nets, Chicago Bulls, Charlotte Hornets, Dallas Mavericks, Detroit Pistons, Golden State Warriors, Houston Rockets, Indiana Pacers, Memphis Grizzlies, Miami Heat, Milwaukee Bucks, Minnesota Timberwolves, New Orleans Pelicans, Oklahoma City Thunder, Orlando Magic, Philadelphia 76ers, Phoenix Suns, Portland Trailblazers, San Antonio Spurs, Toronto Raptors, and Washington Wizards. Out of all thirty games, the New York Knicks won six games against the following teams: Atlanta Hawks, Brooklyn

Nets, Milwaukee Bucks, New Orleans Pelicans, Orlando Magic, and San Antonio Spurs. Although no conclusion can be made in terms of a correlation existing between Twitter fan sentiment and game attendance of New York Knicks' home games, the following scatterplot suggests there at least is a consistently loyal fan base in attendance at Madison Square Garden even in the midst of their team performing at the bottom of the 2018-19 NBA rankings (see Figure 8):

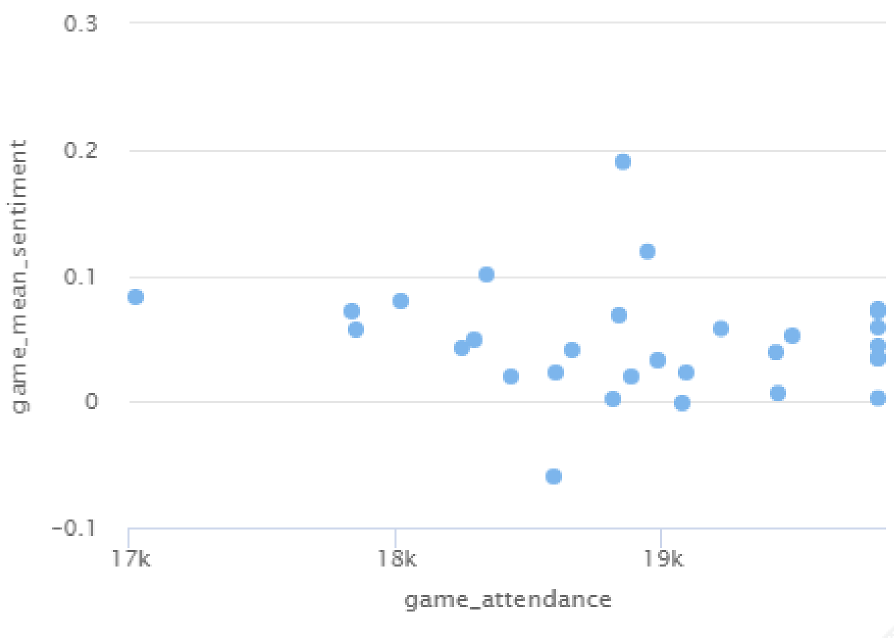


Figure 8: 2018-19 New York Knicks Game Attendance and Game Mean Sentiment Scatterplot

The majority of the points appear to be slightly concentrated at a game attendance greater than 18,000 fans with several points extending beyond the 19,000-mark. Another point to keep in mind is how only one out of all thirty games conveys a mean sentiment below 0 even with the level the New York Knicks were performing at during the 2018-19 season. By examining the mean sentiment of each game and the attendance at each game on an individual basis, one can note the movement of each variable throughout the season. In order to show each variable over time, the date of each game was added into one vector containing the dates of all thirty games. The following line of code was used to convert the manually entered dates into a “date” format that could be read into plots representing a variable over time (see Figure 9):

```
cor_df[['date']] <- as.Date(cor_df[['date']],
                            format = "%Y-%m-%d")
```

Figure 9: Line of Code in RStudio

Having the date vector’s data being converted into an acceptable “date” format was crucial to creating the two following line charts. Beginning with game mean sentiment measured from October 2018 to February 2019, the following line chart shows the dates being displayed on the x-axis while game mean sentiment is being shown on the y-axis below (see Figure 10):

Figure 10: 2018-19 New York Knicks Game Mean Sentiment Line Chart

The next line chart shows game attendance on the y-axis while the dates ranging from October 2018 to February 2019 are being shown on the x-axis. Game attendance additionally relied on having the dates in the correct format to be properly used to create the following line chart in RStudio (see Figure 11):

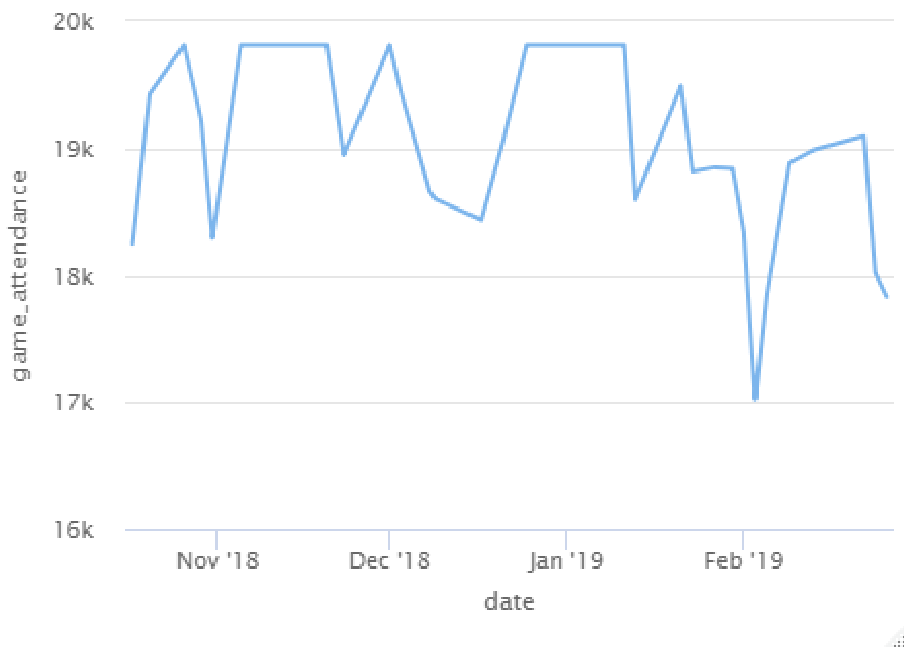


Figure 11: 2018-19 New York Knicks Game Attendance Line Chart

The line charts plotted above indicate both the mean sentiment and game attendance did experience some substantial movement across the thirty-game time frame. One should still notice how the majority of the game attendance numbers remained above 18,000 fans in attendance in addition to the majority of the game mean sentiment values remaining at 0 or above. This even occurred when the New York Knicks held an eighteen-game losing streak at home beginning on December 3rd, 2018 and ending on February 22nd, 2019. These observations highlight how the New York Knicks' ability to retain its fans goes beyond the performance of the team at any given point in time during the present day, bringing attention to its rich history and deep connection to its fans and the city of New York.

INTERPRETATIONS AND CONCLUSIONS

The analyses reinforce the reality all NBA franchises live in that is social media is here to stay and acts as a platform for fans to let franchises know how their team is performing from a customer service standpoint. For the New York Knicks, according to Statista, the team's revenue generation took a substantial hit after the 2018-19 season (see Appendix A) yet as seen in the visualizations regarding fan sentiment and attendance during that same season, the New York Knicks' fan base does not appear to be leaving anytime soon even given the loss in revenue. Revenue generation extends beyond the traditional purchase of a ticket to a game nowadays as NBA franchises are searching for ways to "level up" in nontraditional ways such as leveraging Twitter sentiment to adjust the content they are pushing out onto their Twitter platforms.

In regard to fan engagement, Hypotheses I and II showed the more offensive the Phoenix Suns played by scoring more points and the more victories the Los Angeles Lakers accrued by winning games instead of losing games, respectively, led to noticeable gains in fan sentiment on Twitter. However, one should note the marketer of a franchise cannot influence the sentiment of their fans by relying on team performance alone to boost fan engagement. Instead, the connection between team performance and marketing is the former can partially be used to help guide the latter except only in combination with qualities and attributes that set the franchise apart, irrespective of game outcome. As mentioned in *The Elusive Fan*, attributes independent of competitive outcome enabled marketers to boost fan engagement regardless of whether their team won or lost their games. By applying this notion to fan Twitter sentiment, these two well-regarded franchises may choose to take their fans' Twitter sentiment and study the sentiment to improve and enhance fan experiences inside and outside the arena. During an interview with Paul Epstein, a bestselling author and former NFL and NBA executive, Epstein proposed the following hypothetical question: “let’s say you have a 19,000-seat arena, what if you can deliver 19,000 unique experiences” (P. Epstein, personal communication, August 10, 2021)? This question can be answered with Twitter analytics and sentiment analysis by returning to the Phoenix Suns’ sample from Hypothesis I. A tweet by Andrew Leezus denoted by a sentiment value of approximately 0.592 in regard to the Suns’ 32-point win over the Portland Trailblazers is shown below (see Figure 12):

Figure 12: Tweet by Andrew Leezus ([Screenshot of tweet by Andrew Leezus], 2021)

This tweet mentions players including “Devin Booker,” “Chris Paul,” Mikal “Bridges,” and Deandre “Ayton” in the context of the Suns’ dominant performance and stellar play. Leezus even includes a ten-second video clip of a scene from the movie *Star Wars: Episode VI – Return of the*

Jedi to further express their contentment with the Suns. The quote being pictured is stated by the character Emperor Palpatine which reads “everything is proceeding as I have foreseen.” One user by the name of “Valley Joe” responds to Leezus with the following tweet (see Figure 13):

Figure 13: Tweet by Valley Joe ([Screenshot of tweet reply by Valley Joe], 2021)

Valley Joe responds to Leezus’ tweet by including a GIF of the *Star Wars*’ character Obi-Wan Kenobi saying “hello there” in combination with Valley Joe writing “Playoffs…” in their tweet. Valley Joe appears to be saying “hello” to the Suns’ valid expectation of appearing in the playoffs during that year 2021. The managerial significance extends beyond the fact that these two Twitter users are expressing positive reactions toward the Suns and their performance by rather focusing on **how** they are expressing their reactions. Both users incorporate popular culture in the form of *Star Wars*’ characters to express their positive sentiment with the Suns and their performance. Marketers can use this data to push out marketing campaigns and promotional materials to signify a collaboration between the Phoenix Suns and *Star Wars*. Doing this would allow the Phoenix Suns to tap into the *Star Wars*’ market and fan base to attract fans who may be interested in following the Phoenix Suns. The tweets by Andrew Leezus and Valley Joe hint at how there are fans who already support both *Star Wars* and the Phoenix Suns where more similar fans may exist. These two fans provide a managerial opportunity to create two unique fan experiences based on merging the *Star Wars*' brand with the Phoenix Suns' brand.

If franchises continue to stress the importance of paying attention to how their fans and other spectators are conversing in regard to how well the franchise is performing, the franchises will be able to gain valuable information to improve the way they operate as a business. By improving the customer experience for fans who attend and watch their games inside the arena, this will give a reason for fans to create more positive sentiment by expressing their satisfaction with the team's performance through social media outside the final outcome of a game. Performance in terms of customer experience and community outreach are two vital areas necessary for creating a fan for life. By choosing to take advantage of the data available through Twitter fan sentiment and the textual data itself which brings forth sentiment, NBA franchises can elevate their performance as a business to further align with what their fans want as loyal fans to the franchise.

The ANOVAs reinforced the concept that the NBA requires accountability from its ecosystem of teams who are all being held accountable by their fan base no matter where a game is being played either at home or away on the road. Accountability is enforced by each team competing with each other not only for the Larry O'Brien trophy, but for the retention of basketball fans for generations to come. Based on the ANOVA conducted on the two wins of the New Orleans Pelicans' 2019-20 season against Portland, New Orleans recorded a higher mean sentiment value in their home win versus their away win. Although one may consider the context of winning at home as a leading variable in causing this to happen, sources like *The Elusive Fan* remind marketers of additional attributes that need to be accounted for in measuring fan engagement and loyalty. Fans need to be recognized and understood not only as being engaged in the arena or during game-time, but rather being engaged anywhere at any moment in time. With today's quantity of consumer technology available to the average NBA fan, franchises can achieve keeping their fans engaged as much as possible. For example, by tapping into the Twitter feed fans may receive, a franchise can strive to push out content that entices fans to visit the team's official Twitter page, thus boosting online engagement. Having the ability to write a tweet about one's favorite NBA player from the palm of one's hand is a phenomenon that franchises should look into understanding at a high level to truly make an impact on areas of their business encompassing fan engagement and revenue generation.

LIMITATIONS

One limitation experienced during this project was the inability to precisely track when certain events happened during an NBA basketball game such as the time when the first, second, third, or fourth quarter ended. This limitation caused the original project to undergo several changes to account for the lack of being able to track the precise time of events occurring in a game.

Another limitation experienced during this project was the inability to use version 2 of the Twitter API to create word art visualizations using textual data pulled from Twitter. In order to create these visualizations, the older version 1.1 of the Twitter API was used, requiring a different method of authentication for accessing the API. Although an older version of the Twitter API had to be used instead of version 2 to create word art, the word art visuals were still able to successfully house words pulled from tweets using RStudio and the Twitter API.

Another limitation experienced during this project was lacking access to the revenue generated per game for an NBA franchise. The only data on revenue generation available at the time of writing this thesis were annual reports on revenue generation from Statista. To address this limitation, the project decided to refrain from including a statistical analysis centered on revenue generation due to lacking the necessary data for the analysis. The analysis would have included mean sentiment values as well similar to the correlation test ran in Hypothesis IV regarding the 2018-19 New York Knicks. Fortunately, fan engagement and revenue generation are intertwined to the point where each analysis conducted in this project enabled explanations on revenue generation to be drawn from those analyses.

An additional limitation to keep in mind is certain tweets that are pulled down from Twitter may be completely unrelated to the NBA and its thirty franchises. For example, the word “suns” without being placed in the context of the Phoenix Suns and the NBA can simply mean other phrases and lingo completely unrelated to the Phoenix Suns and the NBA.

FUTURE RESEARCH

Focusing only on key teams like the Phoenix Suns (see Appendix J and Appendix K) and Los Angeles Lakers (see Appendix H and Appendix I) for the first two hypotheses did not account for the remaining twenty-eight teams. The same notion can be applied to the last two hypotheses where only focusing on the New Orleans Pelicans and New York Knicks for Hypotheses III and IV, respectively, does not tell the whole story. Future research on this subject area can begin with running each test from all four hypotheses on every remaining NBA team to account for all thirty teams. During an interview with Michael Meitin, current Senior Associate Athletic Director at Arizona State University and former Director of Group Sales with the

Phoenix Suns, Meitin suggested the following in regard to the New York Knicks in Hypothesis IV: “find teams that have similarities as the Knicks in terms of their win/loss record” and “are the Knicks an outlier or is this something happening across multiple teams” (M. Meitin, personal communication, February 2, 2022)? By running the tests on all thirty teams, further conclusions can be made in regard to why an NBA franchise may be performing at a higher or lower level than another franchise. In regard to the New York Knicks, finding teams who are similar to the Knicks in a variety of areas and understanding any similarities may prove beneficial to future research. Regarding the Phoenix Suns, Los Angeles Lakers, and New Orleans Pelicans, if there are teams who yield similar results to those teams, this observation may determine whether those three teams are outliers or not. A goal associated with conducting this future research is to build a larger sample to locate trends more efficiently that can lead to homing in on a specific variable to be further examined, a strategy also suggested by Meitin. If no new discoveries are made by examining that one specific variable, a new variable can be homed in on to repeat the same process of searching for any new patterns that can determine where certain franchises stand among others in the NBA.

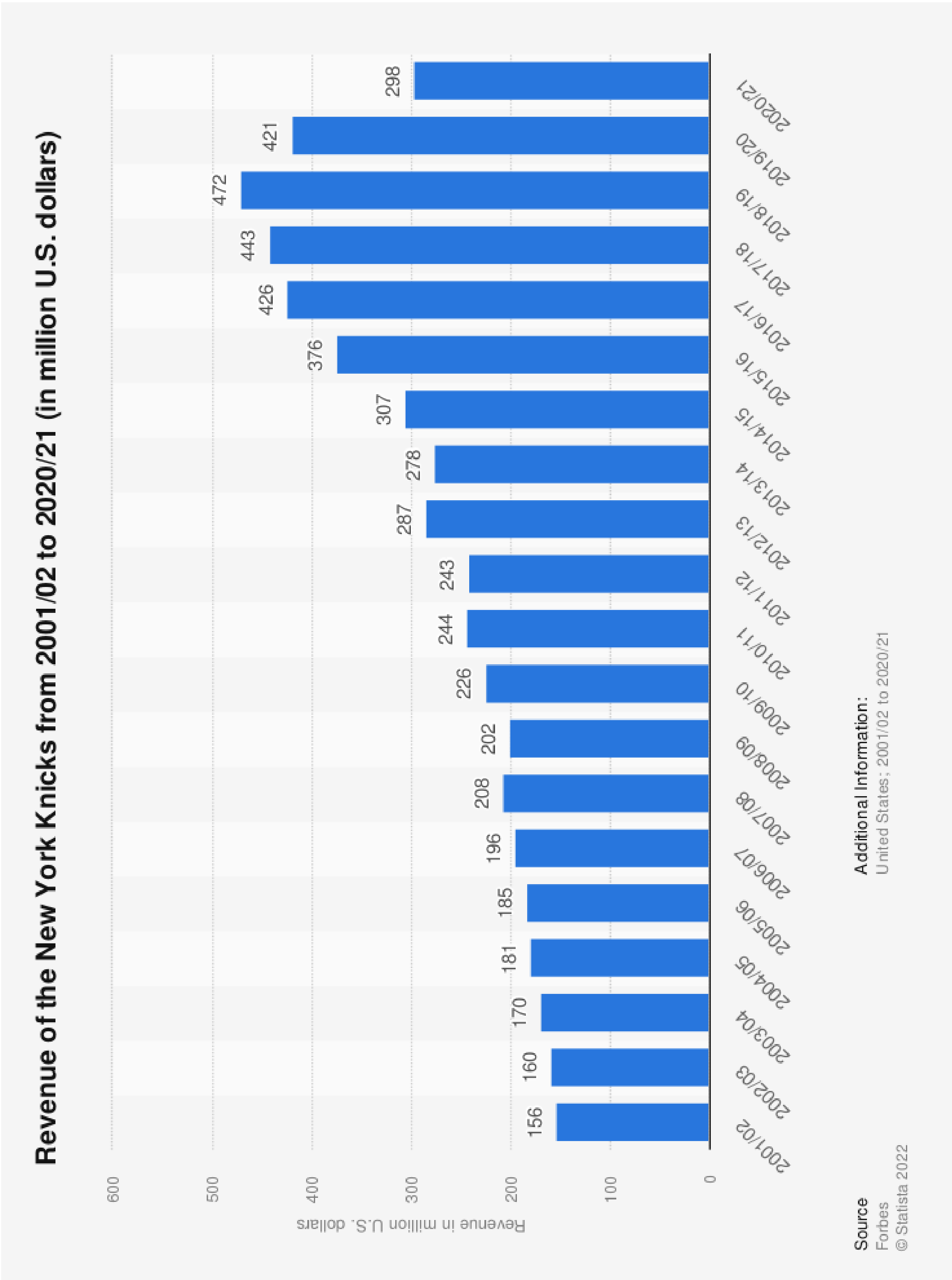
Additional further research may involve diving deep into why certain discrepancies occur which cannot be explained at first glance. For example, according to Statista, NBA regular season ticketing revenue can be seen experiencing an overall decline in the last decade with the steepest decline occurring from 2019/20 to 2020/21 (see Appendix B). However, the number of Facebook fans and Twitter followers of the NBA is on a steady upward trend in the last decade (see Appendix C). By attempting to bridge an understanding between two opposing trends in the NBA, new insights can be drawn that can have a positive impact on improving the league as a whole.

To conclude future research on the point of improving the league as a whole, the basketball players who are fortunate enough to get drafted into the league are in a position of power capable of bringing about positive change to improve the society they live in, beyond the game of basketball. Take for example, the man who decided to open a new public elementary school for children coming from low socioeconomic backgrounds in his hometown, LeBron James (see Figure 14):

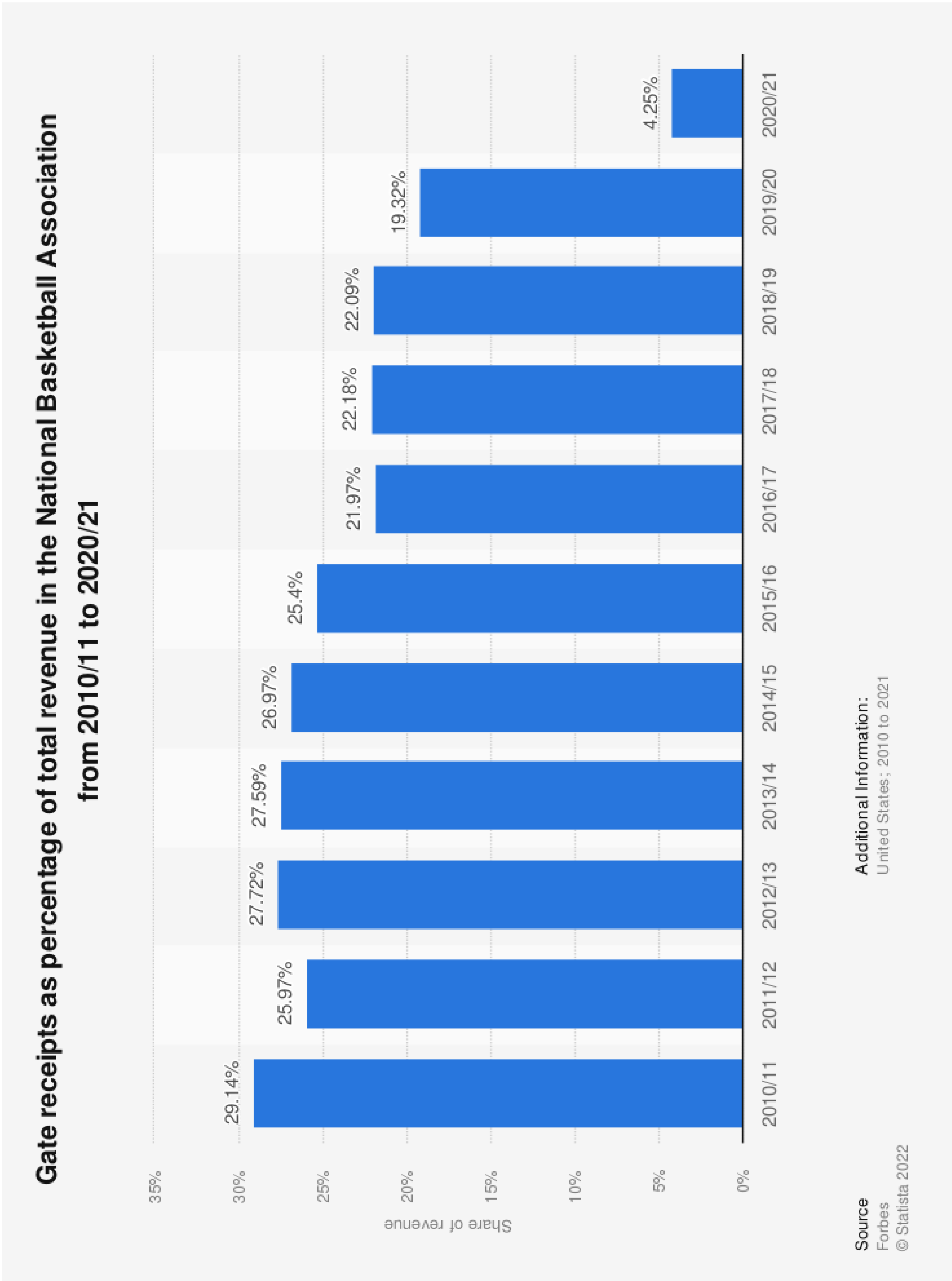
Figure 14: LeBron James (Right) Speaking at the Opening of the I Promise School (*[Photograph of LeBron James speaking at the opening of the I Promise School (IPS)], 2018)*

LeBron James and his persona continues to be discussed by people across the world involving both positive and negative sentiment, especially on Twitter (see Appendix F). LeBron James could have stuck with only playing the game of basketball, yet he decided to do more by imparting a positive impact on his community. For example, James supported the opening of the I Promise School (IPS) in Akron, Ohio in 2018 (see Figure 14), only one of the honorable acts he has done as a driver of social change. After bringing about positive change in his community and for people all over the world, James began to take on a new persona. Instead of only being known as arguably the greatest basketball player of all time, James began to be known as one of the greatest voices of change in a world needing leaders and role models. Future research does not need to conclude with only improving the league, but rather should begin with improving the world the league lives and operates in with the goal of creating a safe and inspiring place for not only basketball enthusiasts to thrive in, but for human beings as a whole to thrive in too.

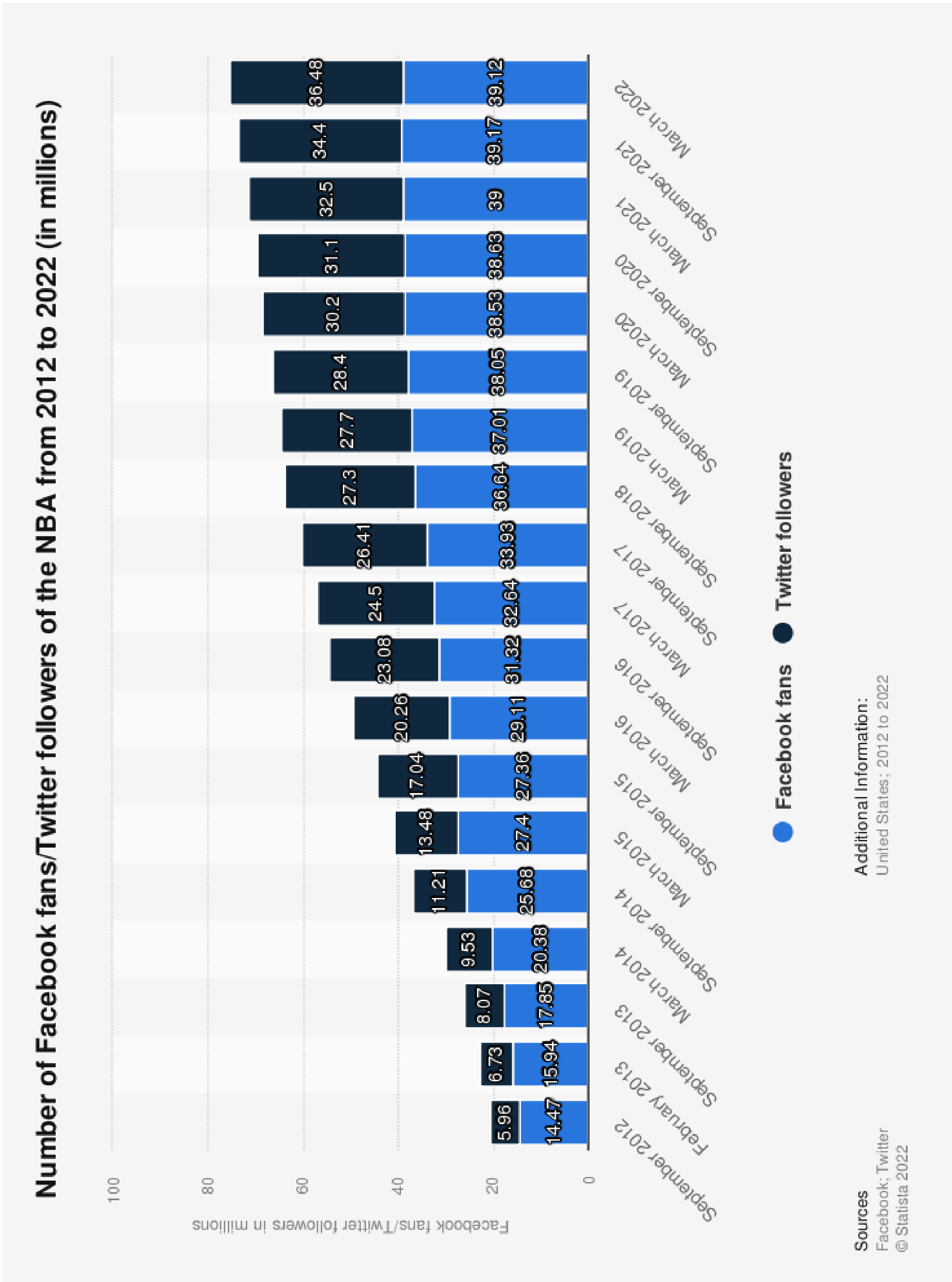
Appendix A: New York Knicks' Annual Revenue from 2001/02 to 2020/21 (Statista, 2022a)



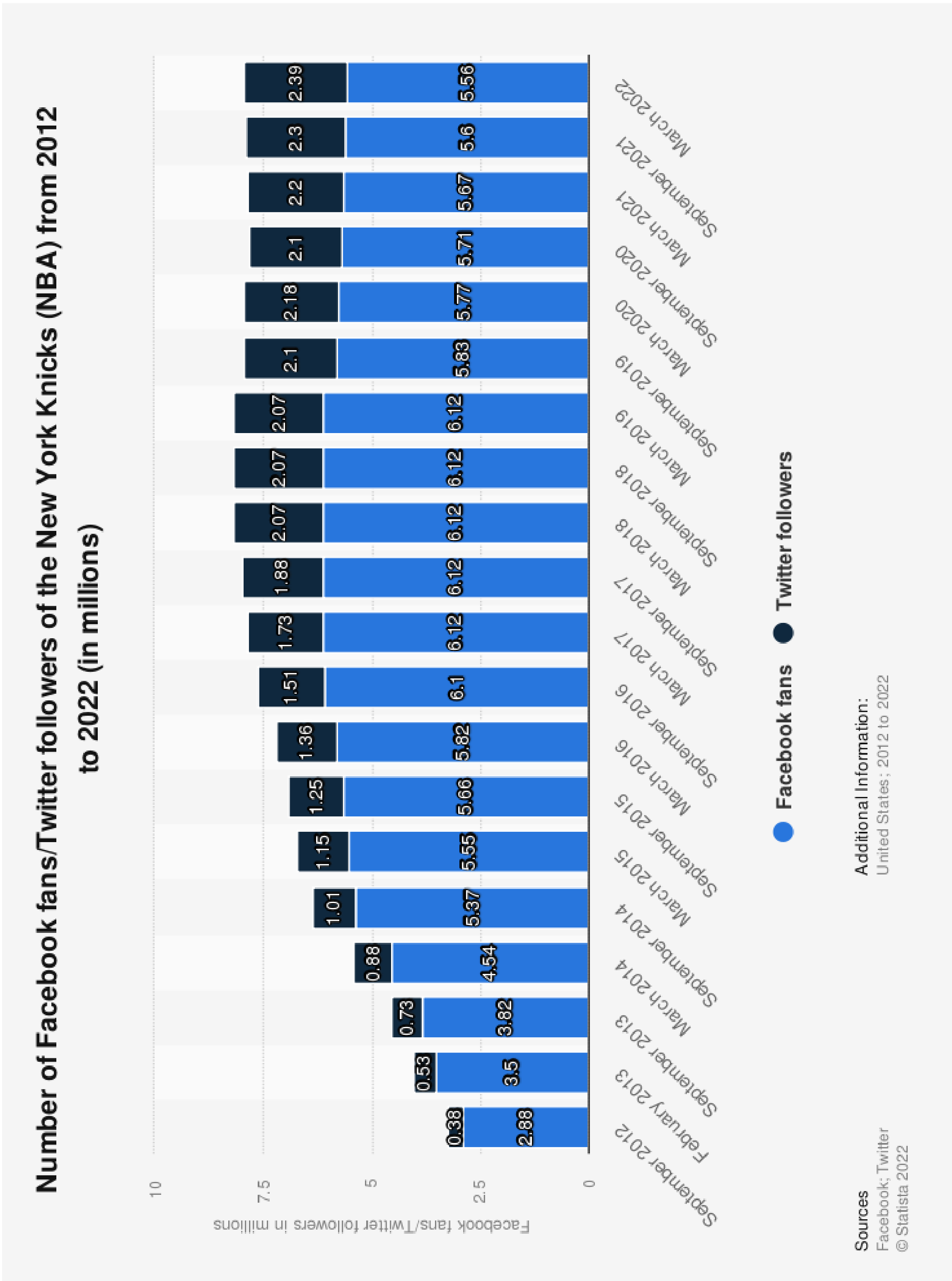
Appendix B: NBA Annual Ticketing Revenue from 2010/11 to 2020/21 (Statista, 2022b)



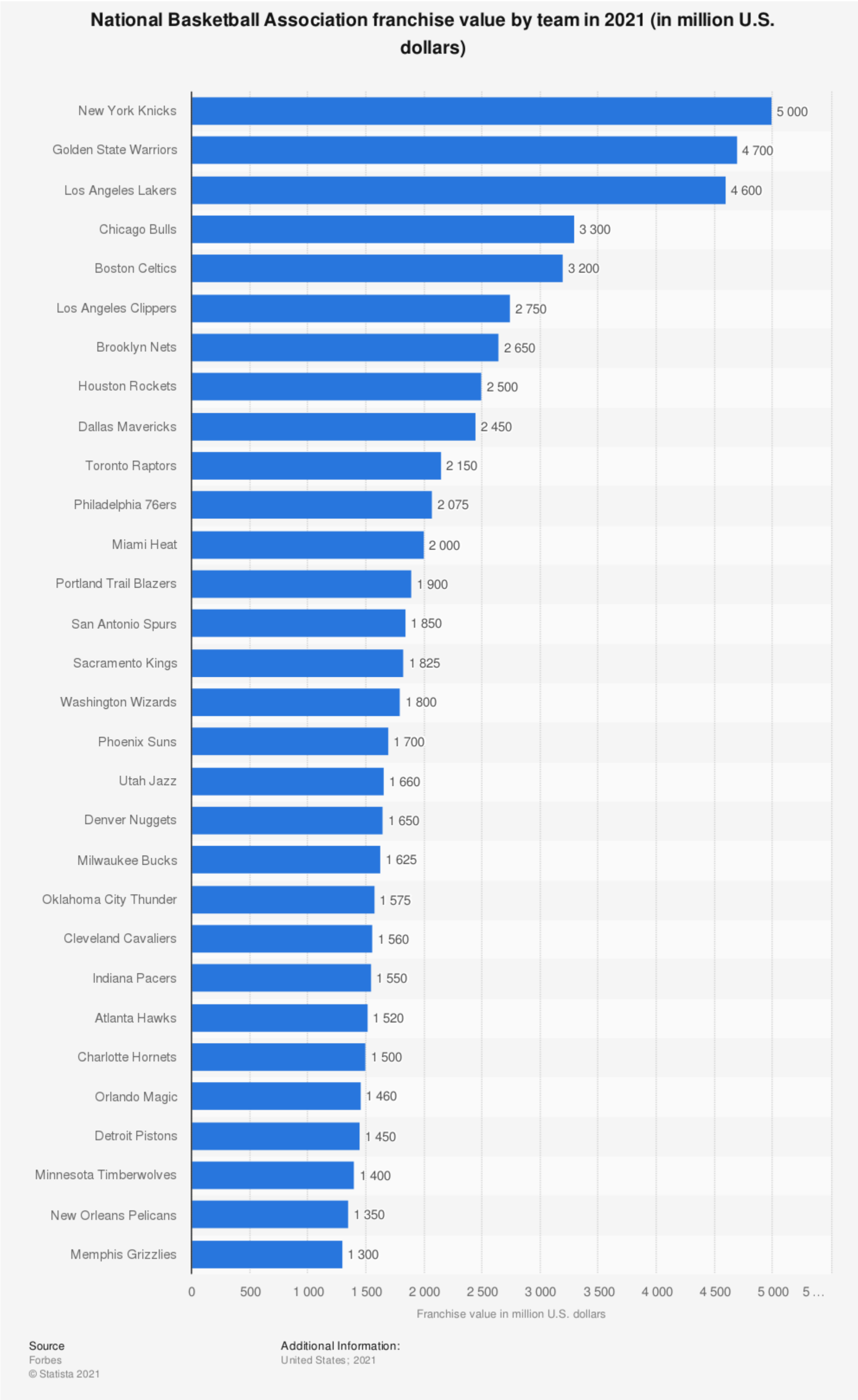
Appendix C: Facebook/Twitter Followers of the NBA from 2012 to 2022 (Statista, 2022d)



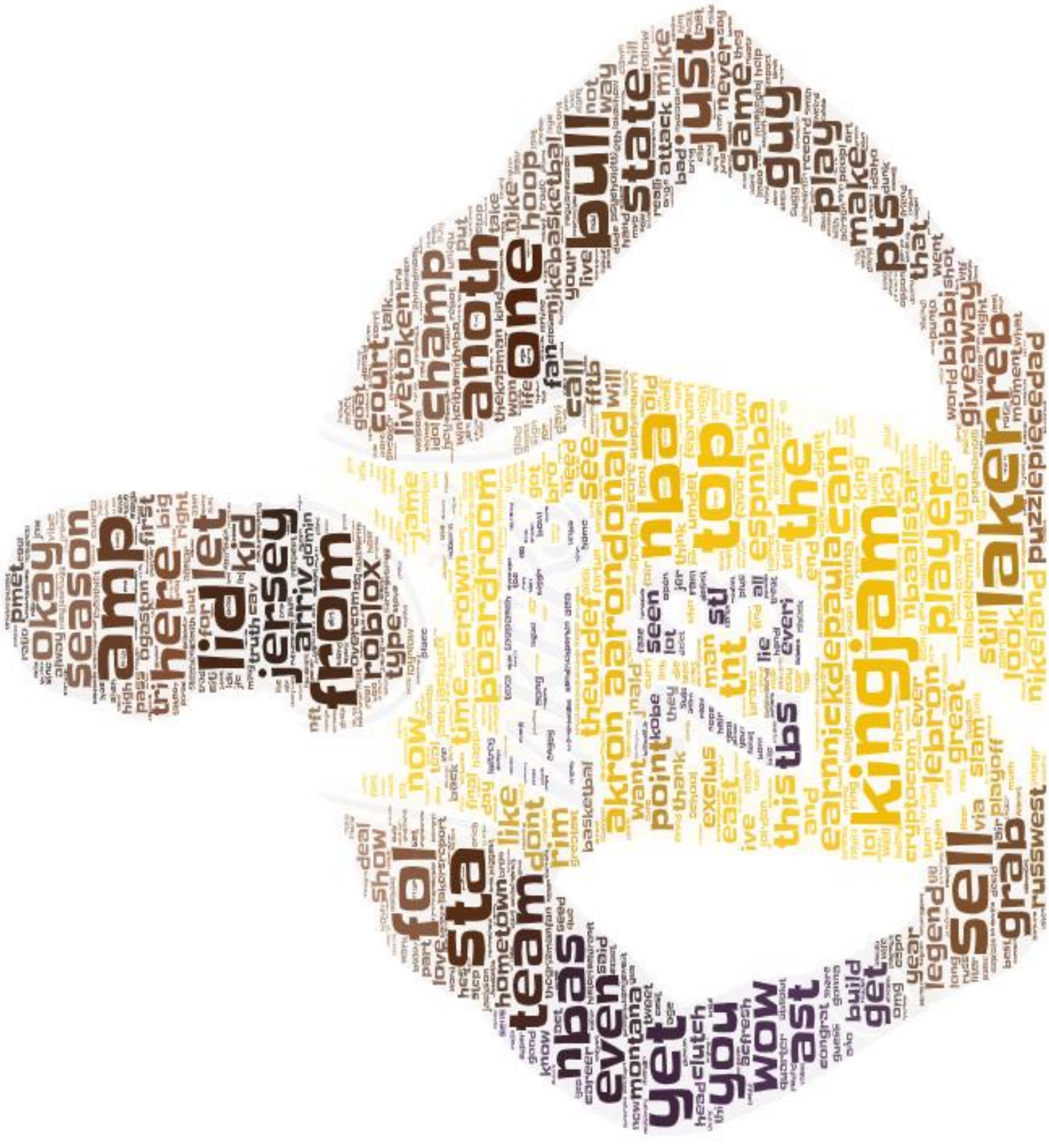
Appendix D: Facebook/Twitter Followers of the NY Knicks from 2012 to 2022 (Statista, 2022e)



Appendix E: NBA Franchise Value Divided by Team in 2021 (Statista, 2022c)



Appendix F: LeBron James Twitter Word Portrait as of Feb. 17th, 2022 (*LeBron James*, 2022)



Appendix G: Screenshot of NO Pelicans' Official Twitter Account (New Orleans Pelicans, n.d.)

Appendix H: Los Angeles Lakers Logo (*Los Angeles Lakers logo*, n.d.)

Appendix I: Los Angeles Lakers Logo Twitter Word Art Using Hashtag (*#LakeShow*, *2022*)

Appendix J: Phoenix Suns Logo (Loodibee, 2022)

Appendix K: Phoenix Suns Logo Twitter Word Art Using Hashtag (*#RallyTheValley*, 2022)

References

Caudill, S. B., & Mixon,Franklin G.,,Jr. (1998). Television revenue and the structure of athletic contests: The case of the National Basketball Association. Eastern Economic Journal, 24(1), 43-50. http://login.ezproxy1.lib.asu.edu/login?url=https://www.proquest.com/scholarly-journals/television-revenue-structure-athletic-contests/docview/198065223/se-2?accountid=4485

Charlotte Hornets. [@hornets]. (n.d.). *Tweets* [Twitter profile]. Twitter. Retrieved March 2, 2022, from https://twitter.com/hornets

Davis, M. A., & Miller, J. (2019). A Conceptual Analysis of Performance Attributes' Influence on NBA Attendance: Why Do Consumers Choose to Attend Games? Journal of Applied Sport Management, 11(2)http://dx.doi.org.ezproxy1.lib.asu.edu/10.18666/JASM-2019-V11-I2-9084

Jain, D., & Singh, S. S. (2002). Customer lifetime value research in marketing: A review and Future Directions. *Journal of Interactive Marketing*, *16*(2), 34–46. https://doi.org/10.1002/dir.10032

Jensen, J., Turner, B., Delia, E., James, J., Greenwell C., McEvoy, C., Ross, S., Seifried, C., Walsh, P. (2016). Forty Years of BIRGing: New Perspectives on Cialdini's Seminal Studies. *Journal of Sport Management*. 30. 10.1123/jsm.2015-0340.

#LakeShow. (2022). WordArt. https://wordart.com/lzcmbtfl2k23/lakeshow

LeBron James. (2022). WordArt. https://wordart.com/rg1hr3g5r3e6/lebron-james

Loodibee. (2022, March 19). *Phoenix Suns logo symbol*. Logos! Retrieved April 2, 2022, from https://loodibee.com/nba/phoenix-suns/phoenix-suns-logo-symbol/

Los Angeles Lakers logo. 1000 Logos The Famous Brands and Company Logos in the World Los Angeles Lakers Logo Comments. (n.d.). Retrieved April 2, 2022, from https://1000logos.net/lakers-logo/

Mishra, S., Khanna, P., Kumar, S., & Sinha, A. (2017). SENTIMENT ANALYSIS: AN APPROACH TO OPINION MINING FROM TWITTER DATA USING R. *International Journal of Advanced Research in Computer Science*, *8*(8), 252-256. doi:http://dx.doi.org/10.26483/ijarcs.v8i8.4716

New Orleans Pelicans. [@PelicansNBA]. (n.d.). *Tweets* [Twitter profile]. Twitter. Retrieved March 20, 2022, from https://twitter.com/PelicansNBA

[Photograph of LeBron James speaking at the opening of the I Promise School (IPS)]. (2018). Chicago Tribune. https://www.chicagotribune.com/sports/la-sp-lakers-lebron-james-i-promise-20180729-htmlstory.html

Pronschinske, M., Groza, M. D., & Walker, M. (2012). Attracting Facebook 'Fans': The Importance of Authenticity and Engagement as a Social Networking Strategy for Professional Sport Teams. *Sport Marketing Quarterly*, *21*(4), 221-231. http://login.ezproxy1.lib.asu.edu/login?url=https://www-proquest-com.ezproxy1.lib.asu.edu/scholarly-journals/attracting-facebook-fans-importance-authenticity/docview/1324536392/se-2?accountid=4485

#RallyTheValley. (2022). WordArt. https://wordart.com/melaj27w520l/ralleythevalley

Reed, D. D. (2016). Matching theory applied to MLB team-fan social media interactions: An opportunity for behavior analysis. *Behavior Analysis: Research and Practice*, *16*(1), 47-49. http://dx.doi.org.ezproxy1.lib.asu.edu/10.1037/bar0000026

Rein, I., Kotler, P., & Shields, B. (2006). *The Elusive Fan: Reinventing Sports in a Crowded Marketplace* (1st ed.). McGraw Hill.

[Screenshot of tweet by Andrew Leezus]. (2021, February 22). Twitter. https://twitter.com/AndrewLeezus/status/1364068189315891200

[Screenshot of tweet by Wadeh Maroun]. (2021, March 28). Twitter. https://twitter.com/wadehs_world/status/1376372186550702082

[Screenshot of tweet by Matthew Warwick]. (2021, February 22). Twitter. https://twitter.com/MB_Warwick/status/1364085785784246272

[Screenshot of tweet reply by Valley Joe]. (2021, February 22). Twitter. https://twitter.com/AndrewLeezus/status/1364068189315891200

Statista. (2022a, February 22). *New York Knicks' revenue 2001–2021*. https://www.statista.com/statistics/196751/revenue-of-the-new-york-knicks-since-2006/

Statista. (2022b, March 3). *NBA regular season ticketing revenue as share of total revenue 2010–2021*. https://www.statista.com/statistics/193410/percentage-of-ticketing-revenue-in-the-nba-since-2006/

Statista. (2022c, March 3). *Value of National Basketball Association franchises 2021*. https://www.statista.com/statistics/193696/franchise-value-of-national-basketball-association-teams-in-2010/

Statista. (2022d, March 8). *NBA number of Facebook fans/Twitter followers 2012–2022*. https://www.statista.com/statistics/322941/facebook-fans-twitter-followers-of-nba/

Statista. (2022e, March 8). *New York Knicks number of Facebook fans/Twitter followers 2012–2022*. https://www.statista.com/statistics/322947/facebook-fans-twitter-followers-of-new-york-knicks/

Wear, H., Collins, D. R., & Heere, B. (2018). What's in a Name? A Case Study of NBA Basketball in Charlotte. *Sport Marketing Quarterly*, *27*(2), 124-134. http://login.ezproxy1.lib.asu.edu/login?url=https://www.proquest.com/scholarly-journals/whats-name-case-study-nba-basketball-charlotte/docview/2131134836/se-2?accountid=4485