RELATIONSHIP BETWEEN PREGAME TWEET CONTENT AND NBA PLAYER PERFORMANCE

by

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(Under the Direction of Patrick O'Connor)

ABSTRACT

A body of research has examined "self-talk" impacts on sport performance, but public communication is less researched. Prior studies have found significant correlations between NBA game performance and sentiment expressed in pre-game tweets, but the performance measures were likely distorted. The purpose was to quantify relationships between sentiment in NBA pre-game tweets and free-throw shooting accuracy. Exploratory analyses examined non-sentiment aspects of tweets and performance. Data from players attempting ≥ 6 free-throws in one or more games during the 2021 - 2022 regular season were eligible. Sentiment scores were generated by the VADER software program, emoji sentiment and sarcasm were rated subjectively. It was concluded that sentiment expressed in tweets was unrelated to free-throw shooting performance. Exploratory analyses supported that higher free throw shooting accuracy was associated with fewer words in tweets, and higher season-long player efficiency ratings were associated with tweets that were easier to read.

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Dedications

I dedicate this paper to my family who have been there for me through it all. Thank you, Mom, Dad, Luke, and all my loved ones for holding me accountable and pushing me to be my best, I love you.

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INTRODUCTION

Purpose and Rationale for the Study

Social media is one of the most prominent sources of communication in today's world. Anyone who has internet access can read publicly available online social media posts from individuals that would otherwise be extremely hard to be in personal, in-person contact with, such as high performing professional athletes. Bodies of research have examined relationships between communication and sport performance (e.g., self-talk) as well as sport performance and psychological states that that often are revealed during communication (e.g., anxiety and confidence). For example, inferring mood states from social media data has been shown to be effective such as studies involving millions of tweets which found more negative words and fewer positive words on Mondays compared to Sundays (Golder & Macy, 2011). Golder and Macy (2011) found consistent trends in mood states across multiple cultures and seasons by using real-time data from personal twitter accounts.

Though there have been studies on determining mood from tweets, there is limited data on the relationship between social media posts from athletes and their performance in the following competition. I am unaware of any prior investigations that have examined relationships between tweets posted on the twitter accounts of National Basketball Association (NBA) players on game days and free throw shooting accuracy. A small body of prior research suggests that positive emotions expressed by NBA

players on game days using tweets may be related to better performance (Xu & Yu, 2015; Xu et al., 2015). However, the performance metrics used in research studies to date are likely to have been substantially biased because of confounding. For example, systematic variations in tweets could have coincided with the expected level of the opponent's performance such as more positive tweets prior to likely wins against weaker opponents. Thus, the primary *apriori* purpose of the present study is to quantify the magnitude and direction of linear relationships between several aspects of pregame tweets and free throw shooting accuracy among NBA players participating in the 2021 – 2022 season. Free throw shooting is the primary focus because performance on this closed skill is not influenced by confounders such as defensive play. Several null hypotheses were tested. Specifically, it was hypothesized (H) that there would be statistically nonsignificant correlations ($P>0.05$) between single game free throw shooting accuracy and the following aspects of pregame tweets:

Hypotheses

H1 The magnitude of the sentiment conveyed in the text of the tweets

H2 The magnitude of the sentiment conveyed by the emojis in the tweets

H3 The magnitude of the sentiment conveyed in the text and emojis combined.

H4 The number of swear words in the tweets

H5 The magnitude of sarcasm conveyed in the tweets

In exploratory analyses, the same hypotheses above were tested but in relation to the 2021 – 2022 season-long player efficiency rating (PER).

Definitions

Tweet: a post on the social media application X, formerly known as twitter

Sentiment: the valence of text or emojis in a tweet; that is, the extent to which the information is judged as expressing positive, neutral, or negative feelings

VADER: a rule-based, machine learning text analysis tool designed to analyze social media style brief text and provide the valence of the overall sentiment expressed

Emoji: a small digital image or icon used to express and idea or emotion

Reading Ease: quantitative measurement of how readable a piece of text is

Closed Skill: a skill performed in a stable or largely predictable environmental setting

Player Efficiency Rating: the rating of a player's per-minute productivity

Free Throw Shooting Accuracy: percentage score based on the number of times a ball shot from the free throw line went in the rim divided by the total number of attempts made

Chapter 2

REVIEW OF RELATED LITERATURE

Social Media and Sport Performance

Self-talk, which involves introspective use of language to influence how an individual feels, thinks and behaves, often to cope with stressful situations (Kross et al., 2014), has been widely studied in relation to sport However, there is a paucity of research examining the extent to which *public* statements are, or are not, related to physical performance. One laboratory experiment found that a public statement about expected leg endurance performance immediately prior to the performance had no effect on leg endurance compared to a condition in which an identical statement was made in private (Weinberg et al., 1980). In the years following the 1980 publication of that research, public statements have become more widely shared and available for analysis by researchers because of the reach and ubiquity of interactive social media technologies and platforms such as Facebook, Instagram, YouTube, and Twitter (Twitter changed its name to X on July 20, 2023. The data in the study described below were from 2021 to 2022; accordingly, the word Twitter will be used throughout this document). Professional athletes today are able to communicate quickly with thousands of fans with no intermediary and this also provides first-hand information to researchers that was not available in the past.

Twitter is a social media platform where personal feelings and thoughts can be posted to a world-wide audience along with emojis, images, and video. The majority of the players in the NBA have an account and are active on this platform. For example, during the 2012-13 NBA season almost 80% of the athletes had an account and

personal control of the posts (Xu et al., 2015). Xu, Yu, and Hoi (2015) found that NBA players would tweet about reactions to games, coach decisions, as well as life and world events that presumably could be impacting the athlete's behaviors, thoughts, and feelings before, during and after games. The informal environment of twitter provides these athletes with a platform to voice their opinions unfiltered by journalists, and potentially including quite personal information reflecting their emotional state (Xu et al., 2015).

Free Throw Shooting Performance Measure

Free throw shooting accuracy contributes to success in professional basketball (Csataljay et al., 2009). Several thousand research studies have examined multiple aspects of free throw shooting and most of this research has been conducted with non-elite level performers. To date, common research themes involving free throw shooting have included biomechanical considerations, such as postural control and ball release properties (Verhoeven & Newell, 2016), variations in the timing between free throws (Wrisberg & Pein, 1992), pre-shot behavioral routines (Gayton et al., 1989), and visual fixation prior to initiating movement (Vickers et al., 2017). Anxiety-related phenomena (Nieuwenhuys & Oudejans, 2017), such as choking under pressure (Goldschmied et al., 2022), also have been given substantial research attention. Related investigations have investigated improving free throw shooting performance using a variety of cognitive intervention strategies such as imagery (Post et al., 2010), mindfulness (Wolch et al., 2021) and self-talk (Galanis et al., 2022).

Player Efficiency Rating

Player efficiency rating (PER) has also been used frequently by researchers as a single index of players' overall performances (Piette et al., 2010). This rating takes the positive accomplishments of a player (i.e., free throws made, 3-pointers, field goals, assists, rebounds, steals, blocks), subtracts the behavioral errors (missed shots, personal fouls, turnovers), and obtains an overall score related to minutes spent on the court and adjusted for the pace of play. PER is one of the most widely accepted measures of overall performance because the statistics take into consideration multiple important elements of game play (Nagarajan & Li, 2017). However, the PER places more emphasis on offensive play and does not account for the strength of the opponent's defense. Consequently, playing minutes against the second team when the game is largely decided could make it easier for a player to achieve better offensive statistics and increase their PER. Regardless, PER has been used to predict team National Basketball Association (NBA) team winning percentage (Nagarajan & Li, 2017), and to quantify the benefits of rest on NBA player performance (Huyghe et al., 2022).

Text Sentiment and twitter Variables

Because language communicates our feelings as well as thoughts, word choice can provide insight into how we feel. Researchers trained in different academic disciplines (e.g. computer science and psychology) have used different terms in referring to subjective feelings. Those terms include affect (Whissell, 1989), mood (Beukeboom & Semin, 2006), emotion (Barrett et al., 2007), and sentiment (Khan et al., 2016). Although some researchers adhere to strict distinctions in the definition and use

of these terms, others do not. Here for the sake of parsimony and because of the lack of widespread agreement and consensus among the different researchers and research traditions, these four terms will be considered as synonyms for the purpose of this paper. A related term, valence, is commonly used to refer to the magnitude of negativity or positivity of the emotion conveyed in a word (Kuperman et al., 2014).

In the Xu, Yu, and Hoi (2015) study mentioned previously, relationships between language used in tweets and aspects of basketball performance were examined based on data from the 2012-2013 NBA season. Pregame tweets, posted from 25-hours to 1-hour before game time, were characterized using a word sentiment scoring system called AFINN. AFINN involves natural language processing, a branch of artificial intelligence. Based on a lexicon, or a data base of words, and rule-based modeling of human language, AFINN gives each word a bipolar sentiment score ranging from -5 (i.e., the word is strongly negatively valenced) to +5 (the word is strongly positively valenced) (Nielsen, 2011). Extensive research has been done to provide a list of normative emotional rankings for a large number of words (Bradley & Lang, 1999) which has been integrated into machine learning tools to be used in studies such as this one. Example words and scores are: bastard (-5), abhor (-3), doubts (-1), wishing (+1), haha (+3) and outstanding (+5). An overall sentiment score was generated for each tweet by summing the ratings of the positive and negative words. A composite measure of overall performance was generated based variables, including the number of games started, minutes played, field goal percentage, 3-point shot percentage and free throw percentage. Unadjusted regression analysis was performed as was a more complex regression model adjusted for variables such as time of day and length of the tweet,

location of the game, and type of tweet (re-tweet, informational, etc.). A significant positive correlation ($p<0.01$) was found between pregame sentiment and overall performance; the magnitude of the relationship was $\beta = 0.17$ and 0.16 in the unadjusted and adjusted regression models, respectively (Xu et al., 2015). In both models, the overall amount of variance accounted for was small (<6%). One key limitation of this investigation was that the performance outcome was potentially biased because it ignored the known performance level of the opponents. In other words, players may have sent more positively worded tweets on the days of games against weaker opponents, and this might have confounded the observed relationships. Also, the free throw percentage results were not presented separately even though free throws are an undefended closed skill that avoids bias associated with the effectiveness of the defensive play of the opponent. Despite the limited number of free throw attempts per game, free throws can have a substantial impact on competition outcomes (Goldschmied et al., 2021). Xu et al. (2015) combined several outcomes to generate a criterion performance measure but included elements unrelated to performance *per se* such as minutes played. There is no consensus ideal measure of overall NBA basketball performance. Using an undefended closed skill, such as free throw percentage, could enhance the accuracy and generalizability of the currently available findings because of fewer biases such as those that can occur on average based on position played (e.g., centers on average score more than guards) or those that have not been measured such as opponent defensive ability and motivation.

In a separate analysis of data from the 2012-2013 NBA season by Xu and Yu, also published in 2015, several changes were made compared to their study discussed

above. In this second Xu and Yu (2015) paper, the sentiment expressed in emoticons used in tweets was converted to a bipolar scale ranging from positive (+2) to negative (-2) scores and this information was included with text information to generate overall sentiment scores. Emoticons are linguistic cues that convey emotional meaning (Aldunate & Gonzalez-Ibanez, 2016) and technically are a sequence of keyboard characters used to illustrate a concept such as a smiling facial expression. Emojis are more recently developed pictographs that can depict more complex concepts including multiple facial expressions, a facial expression with red hearts, sparkles, fire, etc. Basketball performance in this analysis was operationalized using the "plus/minus" metric. The plus/minus metric is based on the net change in game score when a given player is on the court (Okamoto, 2011). The study results found a smaller, though statistically significant, positive association between the game day tweet emoticon sentiment and performance; the standardized β equaled 0.014, the R^2 was unreported. A major limitation of this investigation was that the individual player performance plus/minus metric is inherently confounded by the performance of the four teammates as well as the five opponents (Kubatko et al., 2007). Free throw percentage, which was not reported in second Xu and Yu (2015) paper, is a measure of performance that avoids this limitation.

Emoticons, as used by Xu and Yu (2015), have been found to play a role in interpreting the meaning from short social media messages (Aldunate & Gonzalez-Ibanez, 2016). The limited character count on twitter prior to April 2023 demanded a concise statement from the author and therefore the text may be misinterpreted by different readers without additional contextual information. The addition of emoticons

and emojis provided affective signals that would otherwise be missing without face-to-face communication of the author and reader (Aldunate & Gonzalez-Ibanez, 2016). Aldunate and Gonzalez-Ibanez (2016) found that in the absence of longer statements providing greater context, emoticons and emojis are crucial to determining emotional state in online communication.

The extreme demands made on NBA athletes to travel, train and compete frequently at a high level can produce negative emotions before, during and after performance situations (Morgulev et al., 2022). The use of swear words occurs in the tweets of NBA athletes as they express or emphasize whatever is on their mind. Profanity can represent among the most strongly valenced utterances. Although in most cases swear words are taken as an expression of negative emotion, there are some situations in which swear words can express positive emotions or excitement (Vingerhoets, 2013). Some of the occasions when swearing can be interpreted positively include those involving attempts to increase confidence, augment pain relief, or help to establish one's unique identity (Vingerhoets, 2013). Used in these ways, swearing could reflect positive emotions and plausibly increase the free throw performance of an NBA athlete assuming performance is enhanced by positive emotions as suggested by prior research.

There is a small body of research on swearing and physical performance but the potential effect on free throw shooting accuracy has not yet been tested. There is experimental evidence that swearing immediately prior to performing leads to enhanced strength and power performances in various exercise tests which supports the possibility of swearing as an aid to sport performance (Stephens et al., 2018). These

investigations have not determined if the swearing was viewed to be representing positive or negative emotions. The interpretation of swear words is potentially complex. For example, it has been hypothesized that certain aspects of swearing, such as adding emphasis to a concept or the novelty of the word use, might be key to enhancing performance. There appears to be no science-based information addressing if pregame swearing influences free throw shooting performance in NBA players.

Professional athletes are constantly being evaluated and judged by people who follow their team or athletic career. Many NBA players have thousands, and in some cases, millions of followers on twitter. It is unknown how many players create their own tweets and how many hire someone to manage their twitter account and post on their behalf. Nonetheless, tweets from player accounts often appear to be both a vehicle for personal expression, including mental health struggles (Kamal et al., 2021), and a method to build and support their brand. Effectively managing the impression that followers have of the athlete can significantly increase a player's income (Baethge et al., 2016; Williams, 2016). Thus, players can develop a persona consisting of different characteristics, one of which potentially is being sarcastic. Sarcasm combines irony (defined as the opposite of the literal meaning of words) combined with a condescending tone. Sarcasm is defined by the Cambridge Dictionary as "the use of remarks that clearly mean the opposite of what they say, made in order to hurt someone's feelings or to criticize something in a humorous way."

The use of sarcasm can be common among many people, including in the tweets of some NBA players, although this characteristic of language may not represent the athlete's core persona. Sarcasm has been a business and competition tactic used by

professional athletes if they think it can influence other athletes or the audience they are trying to reach (Guerin, 2016). The use of this type of language on twitter offers an opportunity to examine the relationship between sarcasm and free throw accuracy as an exploratory analysis given there have not yet been any studies on the effects of sarcasm on NBA performance. One key challenge is that the identification of sarcasm is difficult for both humans and computers, though progress continues to be made (Palak Verma, 2021). Attempting to successfully detect sarcasm is an area of interest among those researching social media contexts because it is challenging; for example, there is no way to have in-person contact with most of the people on the internet. Emoticons and emojis have been found to be more expressive than other characters, such as punctuation marks, when trying to evaluate for sarcasm (Aldunate & Gonzalez-Ibanez, 2016). Emoticon and emoji labeling has led researchers to potentially extract greater meaning from tweets, potentially providing a fuller description of player's psychological state from short posts on social media platforms (Huyghe et al., 2022).

In summary, tweets posted on twitter prior to NBA games provide a substantial amount of diverse information that could potentially be related to game performance. Prior research involving the sentiment of the emoticons and text in the tweets from NBA player accounts supports this idea but may be biased in part because of the performance metrics used. Here I re-examine this idea with an *apriori* focus on free throw shooting accuracy. The most relevant published evidence suggests that positively valenced sentiment conveyed either in the text (H1), the emojis (H2) or the combination of text and emojis (H3) in the tweets plausibly could be positively related to better NBA free throw shooting performance. Less direct evidence suggests NBA free throw

shooting performance could plausibly be negatively or positively related to the number of swear words (H4) or the magnitude of sarcasm (H5) expressed in tweets. Given the established circadian variation in both sentiment (McClung, 2013) and athletic performance (Kline et al., 2006) and the fact that tweets are posted with a time stamp, the present study statistically controlled for the number of minutes prior to the start of the game that the tweet was posted.

Lastly, several exploratory analyses were conducted to provide a preliminary examination of novel ideas that have not been previously examined by researchers. Specifically, the five hypotheses above were examined in relation to season-long overall player efficiency rating (PER). I expected relationships to be stronger between the performance in one game which was held no more than 25 hours after a tweet compared to season-long performance. However, the analyses with PER may yield novel information about relationships between tweet content and season-long performance. In some analyses the present study statistically controlled for PER as a potential confound of free throw performance. Also, software used to analyze tweets in the present study provided several outcomes for which there is not prior relevant publications but could yield potentially novel and meaningful data. Accordingly, I also analyzed the number of words in tweets (word count) and the readability of the tweets (reading ease).

CHAPTER 3

RESEARCH DESIGN AND METHODS

Research design

An observational cross-sectional study design was used. Relationships between tweet information and basketball performance was based on real world data in which presumed independent variables (tweets) are not under the control of researchers nor has any randomization been employed such as random assignment to tweet a positive or negative sentiment. Thus, cause-effect relationships cannot be considered based on the results of this study.

Data sources

Tweets were extracted from twitter. Free throw accuracy percentages were obtained from Statmuse (https://www.statmuse.com/nba). Player efficiency rating was obtained from basketball-reference (https://www.basketball-reference.com). The data sets were delimited to the 2021-2022 NBA regular season.

Participants

Included in the study were players whose twitter account sent a tweet within 26 hours prior to a 2021-2022 NBA regular season game in which the player also made at least 6 free throws. A total of 88 NBA players could be included out of a total of 580 players who played in games during the 2021-2022 NBA regular season

(https://www.statista.com/statistics/1334809/nba-players-used/). First, players were identified who took enough free throws, then twitter's advanced search tool was used to find each player's account handle after which tweets were selected.

Procedures and Measures

Tweet and game selections. One pregame tweet from each player, sent from 46-minutes to 26 hours prior to the start time of the game, was used for analysis. NBA policy bans players from using twitter from 1- to 45-minutes immediately prior to the start of the game. A decision was made to limit the analysis to players who attempted at least 6 free throws in at least one game. If players who attempted only one free throw in a game were eligible, then extremes of accuracy would be included in the analysis for these individuals. For example, if only one free throw was attempted the accuracy would be either 0% (0 made out of 1 attempt) or 100% (1 made out of 1 attempt). We judged this approach as unacceptable even though the overall sample size could have been increased. As the number of free throws attempted per game increases the precision of accuracy increases (e.g., if 10 free throws are attempted than accuracy categories have a precision of 10%; 10/10=100%, 9/10=90% and etc...). Thus, this choice of a minimum of 6 free throws per game balanced the need for both an adequate sample size and a minimally adequate free throw accuracy precision. To minimize game selection bias, the total number games that each player who shot at least 6 free throws in a game was entered into Google's random number generator in order to randomly pick one game to include in the analysis for those that had more than one game with at least 6 free throws. One tweet that corresponded to the game selected was chosen for analysis. To

minimize tweet selection bias, if more than one tweet was made from 46-minutes to 26 hours prior to the target game, then each tweet was assigned a number and the Google random number generator again was used, this time to select one tweet at random. This approach was used, rather than averaging all tweets, to be consistent with the statistical assumption that observations should be independent.

Tweet Cleaning. Once the tweets were downloaded and entered into an Excel spreadsheet, they were cleaned by hand to remove extra characters that add error to the analysis. For example, previous studies have shown that the removal of characters that are repeated 3 or more times consecutively (e.g., Scoooore) can be reduced to two characters to enhance the ability of the specialized software to accurately analyze the tweets (Xu et al., 2015). Pure re-tweets were filtered out.

Objective Tweet Analysis. For Hypothesis 1, sentiment analysis of text in tweets was analyzed using a machine learning tool titled Valence Aware Dictionary and sEntiment Reasoner (VADER). VADER is a rule-based test analysis tool designed to analyze social media style brief text and provide the valence of the overall sentiment expressed (Hutto & Gilbert, 2014). At least one study found that VADER outperformed AFINN, a software program used in prior tweet-NBA performance studies (Xu & Yu, 2015; Xu et al., 2015) and which is based on a somewhat different lexicon and statistical model (Srivastava et al., 2022). Consistent with prior research, here VADER scores ≥ 0.05 were interpreted as positively valanced, scores ≤ -0.05 were considered negatively valanced, and the other scores were judged as neutral (Pano & Kashef, 2020). As a check on the VADER analysis and to identify potential instances that might be difficult for the software, the research team blindly rated the tweets to provide a

human evaluated sentiment score. Three researchers ranked the tweets using a score of -1 to represent negative, 0 to represent neutral, and 1 to represent a positive sentiment. The three scores were averaged and compared to the VADER sentiment scores. The largest discrepancies between VADER and human scoring occurred for five tweets. The following three tweets were changed from negatively scored to positively scored:

ID=17 “Nothing better than being a father”.

ID=36 “Fights were on 10 tonight tho”. The human raters concluded there were fights that could be watched at 10 pm that night, so fights were not negative.

ID=67 “#EvanMobley is killing it! Let's send him to #NBAAllStar”. The human raters judged “killing it” to mean good performance, so the tweet was judged as positive not negative despite the generally negative word “killing”.

The following tweet was changed from positively scored to negatively scored:

ID=30 “ Y’all know y’all wrong w/ these Euphoria spoilers” Raters judged this tweet as negative to tell people they are wrong as the emphasis was on the television show “Euphoria”, not the feeling,

The following tweet was changed from neutral to negatively scored:

ID=65 “I have a long way to go”. The raters judged this tweet to be a negative self-statement about the player’s need to improve his performance”.

Qualitative Tweet Analysis. For hypothesis 2, sentiment information based on emojis was analyzed qualitatively. The emoji images were ranked on sentiment using a 5-point Likert scale of very negative (0) to very positive (5). When multiple emojis were used, each one was ranked, and the average was used as the criterion score.

For hypothesis 3, VADER and emoji scores also were combined to create another variable to assess overall tweet sentiment. To put the emoji data on a scale similar to the VADER scale in which negative numbers represented negative emotions, the original 0-5 Likert scale was modified to a -0.75 to 0.75 scale with the following scaling: -0.75 very negative, 0.25 negative, 0 neutral or no emoji, 0.25 positive, and 0.75 very positive.

For hypothesis 4 (regarding the number of swear words) and 5 (regarding sarcasm) the tweets were analyzed by the research team. Sarcasm scores could range from 0 to 5, with 0 representing no sarcasm and 5 being the highest level of sarcasm. Swearing was scored by counting the number of swear words in the tweet as has been done in prior research (Song et al., 2022). For hypothesis 5, a rule based approach that has been used in prior twitter studies was used and this included the context within the twitter feed history as well as punctuation and sentence formation (Palak Verma, 2021).

Exploratory Analysis. Word count and reading ease data are reported outcomes from a program I used called Textalyzer (https://seoscout.com/tools/text-analyzer). The program uses the Flesch reading-ease metric (Flesch, 1948). Text that is easily understood is given a higher reading ease score. Longer statements with more syllables, details and characters are given lower scores indicating the text is more difficult to read. The number of emojis per text was counted by the research team.

Data Analysis

Data were entered into IBM SPSS Statistics (29.0.1.0) which was used for all the analyses. The explore function in SPSS was used to detect outliers (defined as ≥ ± 3 standard deviations from the sample mean) and check assumptions. The swear words,

sarcasm and word count variables were kurtotic and skewed. Only three of the total 88 tweets used swear words. Only 11 of 88 tweets expressed sarcasm. The number of words in tweets was rightward skewed, scores ranged from 0 to 54 and the mean, median and mode, respectively were 9.58, 6.00 and 3. A square root transformation was used to make the word count variable normally distributed. Data transformations were inadequate to make the sarcasm and swear word data normally distributed.

The primary hypotheses were tested for statistical significance using Pearson product moment correlations at a Bonferroni corrected P-value of ≤.01 while the exploratory hypotheses were tested using a P-value of ≤.05. There was greater concern to account for type I error in the primary hypotheses instead of the exploratory because the non-sentiment variables and season performance metric used had not been explored before this study.

The data were also analyzed using t-tests which are more robust to violations of normality. For the t-test analyses, performance groups were created using dummy codes. Free throw shooting performance was divided into two groups using 75% accuracy as the cut point, this was the average free throw shooting percentage among NBA players across the entire association during the 2021 - 2022 season. PER sub-groups also used the league average score, which is set to 15 each season, to define high (>15) and low (≤15) performance groups. Once the dummy variables were created, the t-tests were run in SPSS to compare means of the performance groups with the twitter variables to examine any between group differences.

CHAPTER 4

RESULTS

Table 1 provides the correlation results for free throw accuracy. The five hypothesized null relationships with free throw accuracy all were accepted (all P-values > .05). Exploratory correlations between free throw accuracy, word count **(Figure 1)** and emoji count were small and negative while the relationship with reading ease (r = -0.213; **Figure 2**) approached significance (P=.056). The exploratory and hypothesized correlations were not significantly changed when controlling for the timing of the tweets or when quadratic relationships were considered. When these variables were examined using t-tests (data and P-values provided in **Table 2**), there was no significant group difference for reading ease (P=.904); however, there was a significant group difference in word count, $t(86) = -2.505$, df=63.561, $p<0.019$. The above average free throw accuracy sub-group (n=49; 90.4% ± 7.8% free throw accuracy) on average used about 5 fewer words (7.20 versus 12.56) per tweet compared to the below average sub-group (n=39; 58.4% ± 15.7%) as shown in **Figure 3**. The magnitude of the effect size was d = 0.56.

Table 3 provides the correlation results for player efficiency rating (PER). The five hypothesized null relationships with PER were all accepted (all P-values > .05). When these variables were examined using t-tests (data provided in **Table 4**) there was a statistically significant effect for reading ease, t-value (df = 35.777) = 2.782, $p<0.009$. Tweets from the accounts of players with above average PER were characterized on

average by tweets that were easier to read (n=63, 62.47 ± 43.05) compared to the sub-group with below average PER (n=18, 88.61 ± 32.56; **Figure 4**). The magnitude of the effect size was d = 0.68. Note that only a sub-sample of 81 players could be included in this exploratory analysis of reading ease because seven tweets that only contained emojis could not be included in this analysis.

A sample of tweets and performance information is provided in **Table 5**. Appendix B lists the tweets, free throw accuracy and PER data for each participant.

Chapter 5

DISCUSSION

The primary aim of this study was to examine potential relationships between the free throw shooting performance of NBA players and the sentiment expressed in pre-game tweets. There is a large literature examining the potential role of pre-game behaviors and psychological states and performance extending at least as far back to the 1940's (Johnson, 1949). Prior research has examined performance in relation to a number of pre-performance psychological conditions including arousal (Liane et al., 2009), emotions (Hanin, 2007), anxiety (Raglin, 1992) mood (Hassmén et al., 1998), the induction of mental fatigue using cognitive tasks (Van Cutsem et al., 2017) and private self-talk (Galanis et al., 2022). In the last two decades, social media platforms such as twitter have allowed athletes to make public their precompetitive thoughts and feelings. The present study focused on feelings or sentiments. Previous research in this area has reported that tweet sentiment is related to player performance. One study of nine NBA players with the most minutes in five 2019 NBA playoff games, found that tweet sentiment could predict player performance defined by three offensive metrics (assists, points per game and rebounds divided by minutes played) (Li et al., 2021). Other studies have reported significant relationships between NBA performance and linguistic variables derived from pre-game tweets such as sentiment derived from text (Xu & Yu, 2015) or emoticons (Xu et al., 2015). The results from the present study differ from the prior investigations but that may be due to the fact that the performance metric

of the previous studies was not as unbiased as the free throw accuracy metric used here. Free throw shooting distance is constant in every competition situation and provides a less biased metric than others such as a sum of offensive output or the plus minus metric in part because free-throw shooting is an undefended activity (Xu et al., 2015). Obtaining an optimal measure of performance is an obstacle that occurs often in this area of research. Free throws are an accurate measure that avoids. Some of the biases inherent in performed measures used in prior studies such as plus/ minus or minutes played (Goldschmied et al., 2021).

The main finding from the present study is that the sentiment in tweets, determined from pregame text (H1), emojis (H2), and the combination of text and emojis (H3), is not significantly related to free throw shooting accuracy. This finding could have occurred for several reasons. It is possible that there is no true relationship between sentiment expressed in tweets and free throw shooting performance. One alternative is that a relationship truly exists, but the timing of the free throws was too long after the tweets posted for the relationship to be captured. At least one investigation examining the temporal patterning of pre-competition moods on performance found that mood data obtained one day prior to competition better predicted performance than data obtained either one week or one hour before competition (Keikha et al., 2015). Also, more data may need to be included for these relationships to emerge as reliable. For example, in two other studies significant relationships were documented between sentiment and NBA performance when data from multiple games across the season were included (Xu & Yu, 2015; Xu et al., 2015). Future research could examine relationships between tweet sentiment and free throw performance across multiple games during a season.

Potential relationships between free throw shooting performance and either sarcasm (H4) or swearing (H5) could not be well tested because of the limited amount of these linguistic elements in the sampled tweets. There were only three tweets with swear words in the sample and the prevalence of sarcasm was also too small to provide a compelling conclusion about these outcomes.

Tweet sentiment variables were also considered in regard to overall performance assessed using the player efficiency rating (PER). This exploratory analysis found that PER was unrelated to all the sentiment measures (H1 – H5). One obvious potential explanation is that only one pregame tweet was included in the analysis while the PER was based on season-long performance. Given the well-established fact that affective valence is often characterized by substantial hour-to-hour and day-to-day data variability (Larson et al., 2015) the chances of finding statistically significant relationships between sentiment and PER would have been improved if additional tweet data were included in the analysis. Variability of mood over time could also have an impact in itself on the strength of this relationship (Golder & Macy, 2011) because these tweets were obtained up to 26 hours before tip-off time.

One exploratory analysis of non-sentiment variables showed that the sub-group whose free throw shooting performance was above the NBA average of 75%, the subgroup with an average of 90.4%, had about five fewer words (7.20 versus 12.56 words) in pregame tweets compared to the sub-group of players who exhibited below average free throw shooting performance (58.4%). There is no prior research concerning tweet length and subsequent athletic performance that can be compared to the present results. One report on twitter by a google employee based on over one

million tweets found that the average tweet length was 140 characters which is estimated to be characterized by about 20 to 35 words (https://twitter.com/isaach?lang=en). These data suggest that the twitter accounts of NBA athletes, whether below or above average in free throw shooting performance, publish shorter tweets than non-athletes. Other evidence shows that shorter tweets about politics result in more engagement such as greater retweeting (Force, 2012). Speculatively, when tweets from players' twitter accounts are short, and therefore designed to optimize engagement, the players' social psychobiological state may be advantageous for better free throw shooting. This relationship could also point to the specific focus of the athlete before a game. It is possible that those athletes who are tweeting more extensively are trying to make a name for themselves, promote their sponsors, or explain personal anecdotes. Anecdotally, our data of tweets that had a higher word count were mostly business promotions or personal life stories. A specific mechanism for this potential relationship is currently uncertain.

Another exploratory analysis in the present study found that the sub-group that was above the NBA average on overall performance as measure by PER during the 2021-2022 season was characterized tweets that were easier to read than the sub-group of poorer performers. The tweets from both groups can be interpreted as being easily understood by 13- to 15-year-old students. The idea of readability, or reading ease, has been studied by many linguistics researchers and has been found to be a successful tool in linguistics. The Flesch readability scale used by Textalyzer is one of the most popular and validated measures (Yu, 2014). The approach uses a model that gives values to the number of words, the sentence length and number of syllables per

word in order to account for the level of complexity and difficulty (Yu, 2014). Experimental evidence supports that tweets on popular topics, such as Black Lives Matter, COVID-19, K-pop, Bollywood movies, gaming, and U.S. politics, that are easier to read result in greater engagement compared to those that are more difficult to read (Firouzjaei & Özdemir, 2020; Sahinuç & Toraman, 2021). It seems plausible that higher PER players or their sport organization, often with a greater following on twitter, either strive to convey a very clear message in tweets in order to best support their image and brand or these players may more often have a team or hire people who do this on their behalf (Wang & Zhou, 2015). This relationship could also relate back to the conciseness of the tweets. Readability and word count are highly correlated as the more information that is provided by the author leads to higher readability score. As both of the exploratory relationships that were significant have a negative correlation there may be value in the length and ability to understand tweets in determining their pre-game focus and intent in tweeting.

LIMITATIONS

One limitation was that tweets were scraped from NBA players twitter accounts, and it is unknown if the player truly sent the tweets from the account. There is the possibility that someone else controlled these accounts or that a primary purpose of the account was not to accurately convey sentiment but rather to promote the players brand. Other published data has suggested that NBA players often control their twitter accounts, and this activity can influence performance. For example, the finding that

when NBA players sent late night or early morning tweets their next day game performance was worse (Jones et al., 2019).

A second limitation was that free-throw performance in one game relies on a relatively few number of trials. We excluded players with less than six free throw attempts, nonetheless dozens of trials may be needed to obtain representative and reliable free throw shooting performance. The approach used was purposefully chosen to avoid a different limitation, that of bias in other game performance metrics that depend on how well the defense plays. Obtaining an accurate measure of performance is an issue that arises in sports and performance due to the many variables that contribute to competitions. Though this measure may not account for the entire game performance, it is less biased than other measures that have been used in previous studies. The variation in measures for this variable could be a reason that the results are different in our study compared to Xu (2015), and show that finding an accurate measure is crucial to obtain accurate results.

A third limitations is that the approach taken prevented a random selection of NBA players, limiting the generalizability of the findings. About 75% of the players had above-average PER, thus the present study oversampled better NBA players.

CONCLUSIONS

The primary aim of this study was to examine potential relationships between sentiment expressed in pre-game tweets and free throw shooting performance of NBA players. It was concluded that sentiment expressed in one randomly selected pre-game tweet was not meaningfully related to free-throw shooting performance during the game.

An exploratory analysis supported that higher free throw shooting accuracy was associated with fewer words in pre-game tweets. Additional exploratory analysis revealed that one pre-game tweet was not meaningfully related to season-long player efficiency rating (PER) but that tweets that were easier to understand were associated with higher PER scores.

Table 1. Correlations between free throw accuracy and tweet-related outcomes (n=88).

	FT accuracy	Text sentiment	Emoji sentiment	Text + Emoji sentiment	Word Count	Emoji Count	Read Ease	Sarcasm	Swear Word Count
FT accuracy									
Text sentiment	-0.090*								
Emoji sentiment	0.137*	0.240*							
Overall sentiment (text + emoji)	0.011*	0.847**	0.719**						
Word Count	-0.136**	0.472**	-0.077	0.295*					
Emoji Count	-0.031	-0.161	0.515**	0.167	-0.240*				
Reading Ease	-0.213**	0.037	-0.018	0.018	0.162	0.017			
Sarcasm	-0.109*	-0.046	-0.119	-0.099	-0.021	-0.071	0.169		
Swear Word Count	0.008*	-0.153	-0.239*	-0.241*	-0.041	-0.078	-0.049	0.028	
Tweet timing (minutes prior to game)	-0.019	0.006	0.013	0.012	0.029	-0.052	0.105	0.073	-0.033

*P<.05; **P<.001

Table 2. Descriptive statistics, Cohen's d effect size, and P-value from independent t-tests for low and high free throw accuracy groups.

Variable	Below average free throw group (n=39)	Above average free throw group (n=49)	Cohen's d / P-value
Sentiment (text)	0.235 ± 0.430	0.179 ± 0.383	0.136 / 0.519
Sentiment (emoji)	0.101 ± 0.342	0.172 ± 0.279	0.231 / 0.285
Overall sentiment (text + emoji)	0.337 ± 0.611	0.352 ± 0.528	0.026 / 0.903
Word count	12.56 ± 11.984*	7.20 ± 8.026*	0.538 / 0.019*
Emoji count	0.87 ± 1.151	0.76 ± 1.146	0.102 / 0.637
Swear word count	0.05 ± 0.223	0.02 ± 0.143	0.169 / 0.434
Reading ease	70.73 ± 37.230	66.41 ± 45.944	0.102/ 0.642
Sarcasm	1.28 ± 0.793	1.18 ± 0.667	0.136 / 0.529

*P<.05

Table 3. Correlations between performance efficiency ratings and tweet-related outcomes (n=88).

	PER	VADER	Sentiment (emoji)	VADER + Emoji	Word Count	Emoji Count	Reading Ease	Sarcasm	Swear Word Count
VADER	-0.015*								
Sentiment (emoji)	0.118*	0.240*							
Sentiment (VADER + emoji)	0.054*	0.847**	0.719**						
Word Count	-0.160	0.472	-0.077	0.295**					
Emoji Count	-0.002	-0.161	0.515**	0.167	-0.240*				
Reading Ease	-0.174**	0.037	-0.018	0.018	0.162	0.017			
Sarcasm	-0.076*	-.046	-0.119	-0.099	-0.021	-0.071	0.169		
Swear Word Count	0.100*	-.153	-0.239*	-0.241*	-0.041	-0.078	-0.049	0.028	
Tweet timing (mins prior)	-0.088	0.006	0.013	0.012	0.029	-0.052	0.105	0.073	-0.033

*P<.05; **P<.001

Table 4. Descriptive statistics for the high and low performance efficiency rating groups.

Variable	Below average PER group (n=21)	Above average PER group (n=67)	Cohen's d / P-value
Sentiment (VADER)	0.167 ± 0.279	0.216 ± 0.436	0.121 / 0.549
Sentiment (emoji)	0.167 ± 0.299	0.133 ± 0.313	0.109 / 0.664
Sentiment (VADER+emoji)	0.334 ± 0.422	0.349 ± 0.604	0.026 / 0.916
Word count	9.33 ±10.777	9.66 ± 10.187	0.031 / 0.901
Emoji count	0.90 ± 1.411	0.78 ± 1.056	0.112 / 0.655
Swear word count	0.00 ± 0.00	0.04 ± 0.208	0.245 / 0.083
Reading ease	88.61 ± 32.56*	62.47 ± 43.05*	0.637/ 0.009*
Sarcasm	1.29 ± 0.902	1.21 ± 0.664	0.106/ 0.721

* statistically significant

Table 5. Tweet examples for a sub-sample of the study participants.

Name	Tweet	Free throw accuracy	Performance efficiency rating	PER group (1=above average)
Kevin Durant	“incredible”	90%	25.6	1
Trae Young	“another day, another opportunity”	83%	25.3	1
Steph Curry	“Lock in! #dubnation”	100%	25.3	1
Willy Hernangomez	“Grande”	100%	22.3	1
Lonnie Walker IV	“First time at fiesta wow!! Amazing and to the community and fans love y’all. You guys made the experience even better. Thank you to the city of SA for welcoming me in with such open arms it means a lot !”	66.70%	12.3	0
Andre Drummond	“Weirdo vibes… I use to respect your page, but you are no longer credible. Trying to capitalize on false info…”	54.50%	21	1

Mitchell Robinson	“Positive vibes let’s make it a great Monday and game day”	50%	20.9	1
Josh Hart	“The best way to find yourself is at the bottom of the wine glass”	33.3%	16.1	1

Figure 1. Scatterplot depicting the relationship between free throw shooting accuracy and the number of words in tweets (r = - 0.136, P=0.205). About 19% of players (17/88) were 100% accurate creating a potential ceiling effect.

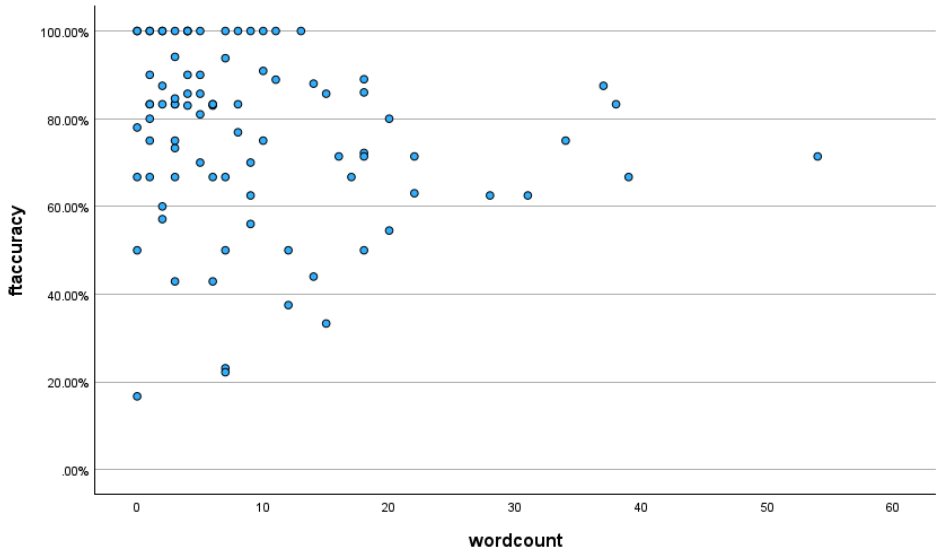
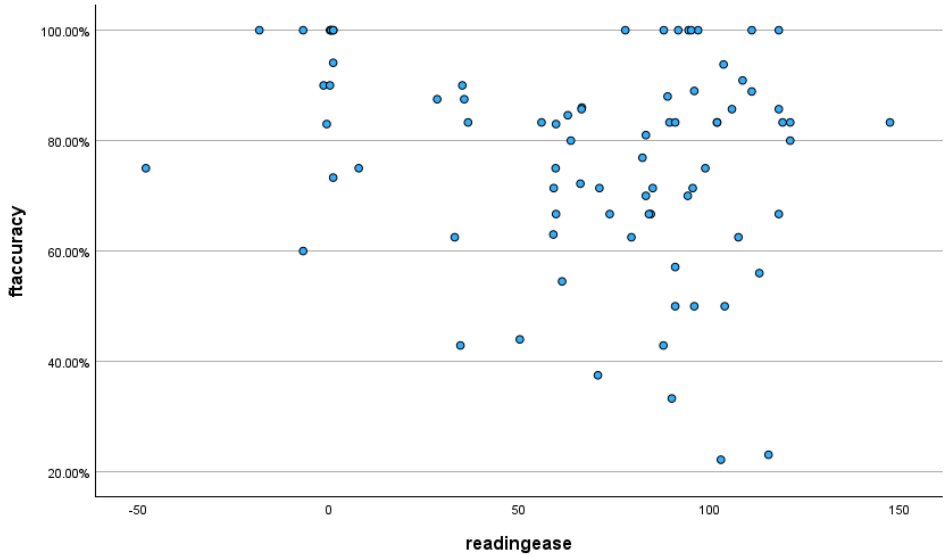


Figure 2. Scatterplot depicting the relationship between free throw shooting accuracy and reading ease (r = -0.213, P=0.056). The higher the readability score, the easier a tweet is to read and understand.



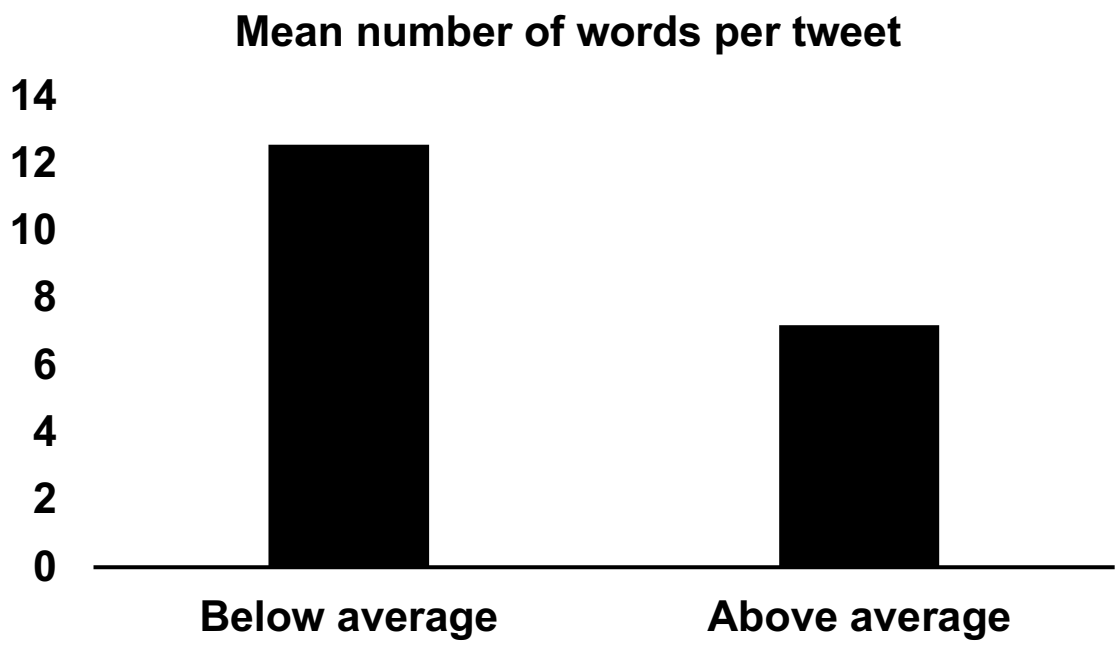


Figure 3. Mean number of words in pregame tweets in the sub-group (n=39) with below the NBA season average (75%) and the sub-group with above the average (n=49) free throw shooting during the target game.

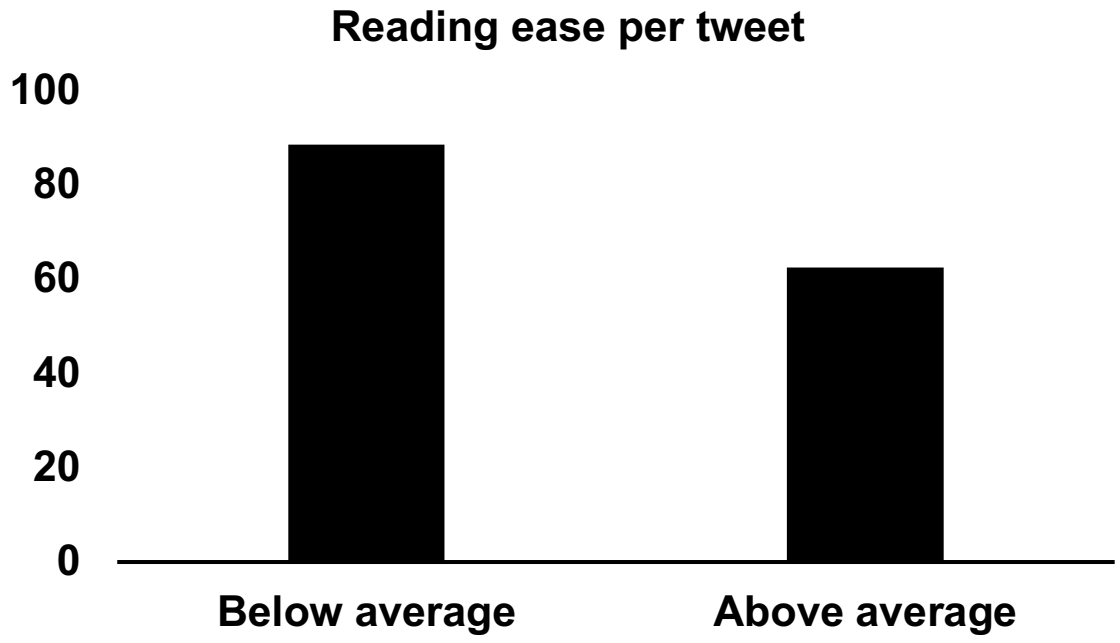


Figure 4. Reading ease in tweets from the accounts of NBA player sub-groups with above- (n=63) and below-average (n=18) performance efficiency ratings. Lower scores indicate that a tweet is easier to read.

Appendices

Appendix A: Frequency distribution of free throw shooting accuracy scores

Appendix B: Player tweets, free throw accuracy and performance efficiency rating.

Name	Tweet	FT%	PER
Kevin Durant	Incredible	90	25.6
Danilo Gallinari	Less impact on the environment. More impact in your style.	100	16.3
Trae Young	Another Day, Another Opportunity	83	25.3
Desmond Bane	TCU nicee	100	17.5
Stephen Curry	Lock in! #DubNation	100	21.3
Kentavious Caldwell-Pope	Emojis only	78	12.5
Immanuel Quickley	OT	100	14.5
James Harden	BALLIN LIKE MARCH MADNESS	90	20.9
Damian Lillard	Aww hell Na	73.3	18.4
DeMar DeRozan	S/o Dwill!	94.1	23
Tyler Herro	I caught the vibe y'all giving off and I'm tryna make myself less like it.	50	
Fred VanVleet	MVP	100	17.3
Grant Williams	Nah this is tough	85.7	11.3
Devin Booker	Congrats @CP3 on 3rd all time assist. Shit is amazing and inspiring. Thank you	88	21.3
LaMelo Ball	i see you gangg	100	19.7
Kristaps Porzingis	Im so excited to play ball in this city! I appreciate all the support so far #DCAboveAll	86	23.7
Marcus Morris Sr.	Nothing better than being a father.	83	13.6
Jimmy Butler	all star break done. but I'm just getting started with this TAG Heuer connected watch #TagHeuerConnected Calibre E4	80	23.6
Zach LaVine	New Year's Eve Heave!! @DeMar_DeRozan	100	20
Donovan Mitchell	Naa Trae chill!! @TheTraeYoung	100	21.5
Malcolm Brogdon	Impact is my why, and one of my proudest accomplishments in life is founding the @BrogdonFamFnd . Proud to share more about Brogdon	75	18

	Family Foundation this #GivingTuesday. Please help us give families Hope for the Holidays		
Terry Rozier	Sick to my stomach	100	17.5
Cole Anthony	Gotta do more played lazy	81	13.5
Chris Paul	Congrats @VAUnion1865	87.5	20.8
Bojan Bogdanovic	Srecna Nova godina!! Mnogo radosti i veselja vam zelim!! "Happy New Year! I wish you much joy and joy !!	100	15.6
Mikal Bridges	Hold up … u was wilding like that ?? @Colling1021 omg	83.3	14.5
Paul George	Doing work on and off the court. Today @Reggie_Jackson and I invited families to pre screen #KingRichard.	72.2	18.5
Gordon Hayward	Feels like my first game all over again. Can't wait to hear the roar of the crowd. It's been too long. Bring it tonight, Buzz City! #AllFly	62.5	15
Kyle Lowry	Thanks my brother	83.3	15
Tobias Harris	NFTs are the future if you ask me, any hate toward it I could care less about.	71.4	15.9
Tyrese Haliburton	Y' all know y' all wrong w/ these Euphoria spoilers	100	18.2
Jayson Tatum	The game missed Klay. Happy to have you back champ!	90.9	21.8
Jerami Grant	The greatest team ever assembled	85.7	16
Kevin Love	Legacy Lives Forever #MLKDay @ Equality	100	19.6
Herbert Jones	Headshot!!	83.3	12.3
Bradley Beal	Everybody has talent, but ability takes hard work. #jumpman	62.5	17.4
Jalen Brunson	Fights were on 10 tonight tho	83.3	17.1
Karl-Anthony Towns	Cuando hay hambre, no hay mal pan "When there is hunger, there is no bad bread"	93.8	24.1

Harrison Barnes	Proud our campaign @giveustheballot has raised over $1M for grassroots organizers fighting voter suppression! Help us get to the next million so we can protect the vote for midterms and beyond. #GiveUsTheBallot	83.3	15.7
D'Angelo Russell	That's love man, glad I could be apart of it	100	16.3
Joel Embiid	GO PACK GO	83.3	31.2
Jaren Jackson Jr.	Rush hour a Christmas movie on vibe alone	76.9	17
Miles Bridges	810	83.3	17.9
Trey Lyles	Seeing Red 313 @ Detroit, Michigan	90	16.4
Marcus Smart	More doors or more wheels? Or… more ball screens set in a game or rebounds?	85.7	13.6
Anthony Edwards	We celebrating tonight! These hoopers are going to @McDAAG 2022: @Mark_mitchell25 @D1_Ruby2 @iamKijaniWright @Ashlon3Jackson @_CamWhitmore_ . It's your time now, go get it. #ad	63	16.4
Spencer Dinwiddie	Think about 365 days ago. Even you didn't see it going like this lol #mffl @ Washington D.C.	66.7	15,1
Terance Mann	Let's goo	83.3	13.4
Jalen Suggs	It just hit me that I'm gonna be on @nbatopshot soon	100	8.6
Jrue Holiday	Happy Holidays.	60	19.8

Jaylen Brown	What shoe brand should I wear on Christmas? #tagthem	75	18.9
Pascal Siakam	My #NBAAllStar reserves predication My wildcards West Dame Dbook East Lamelo Randle	44	20.2
Ja Morant	@jarenjacksonjr & @DBane0625 SHOOTAS	75	24.4
Josh Hart	The best way to find yourself is at the bottom of a empty wine glass	33.3	16.1
Lebron James	Dayumm I'm excited to play tomorrow on Xmas!! It just hit me. Merry Xmas to everyone! Love y'all	89	26.2
Bam Adebayo	1	80	21.9
De'Aaron Fox	I always knew my mom was strong. After battling cancer, she only got stronger. Thank you @playerstribune @americancancer @amgenoncology for sharing her story and why early detection is so important. #AmgenSponsored #HealthEquity	87.5	17.4
Luka Doncic	HALA MADRID!!!	57.1	25
Aaron Gordon	__ already!	75	15.3
Deandre Ayton	Standin on business	42.9	22
Montrezl Harrell	Man shit is never enough!	70	23.2
Giannis Antetokounmpo	Thank you Milwaukee	84.6	32.1
Rudy Gobert	Emojis only	100	24.8
RJ Barrett	My bro is like that @AndrewNembhard	66.7	13.6
Russell Westbrook	The city of Los Angeles not only shaped my game,	62.5	14.9

	but continues to shape basketball culture. Now it's your turn to take the game further… #WhyNot? Go Hoop! @Jumpman23 @honorthegiftco		
Christian Wood	I have a long way to go .	23.1	19.1
Jusuf Nurkic	@trailblazers center Jusuf Nurkić has cleared health and safety protocols, sources (PCR) tell me.I'm expecting to play Monday night against Atlanta.	71.4	20.1
Jarrett Allen	#EvanMobley is killing it! Let's send him to #NBAAllStar	37.5	23.1
Wendell Carter Jr.	Emojis only	66.7	18.4
Kyle Kuzma	Not a show better than euphoria .	66.7	33.4
Ricky Rubio	…	100	13.9
Will Hernangomez	Grande @Carlossainz55	100	22.3
CJ McCollum	Y'all are sick	66.7	18.3
Mitchell Robinson	positive vibes let’ s make it a great Monday and game day	50	20.9
Myles Turner	From my very first CD (s/o @gwenstefani) to my sports hero, this is My Firsts with @PlayersTribune.	71.4	17.5
Isaiah Jackson	Bad days makes the good days way more exciting	70	20.6
Jas'Sean Tate	I take it back that was a good block	56	14.3
Patrick Beverly	Emojis only	50	14.8
Onyeka Okongwu	Emojis only	66.7	19.8
Clint Capela	Back at it … GAMEDAY in the A!!	42.9	21.4
Andre Drummond	Weirdo vibes… I use to respect your page , but you are no longer credible . Trying to capitalize on false info …	54.4	21
Nassir Little	Idk why this is so funny	83.3	13.5
Lonnie Walker IV	First time at fiesta wow!! Amazing and to the community and fans love	66.7	12.3

	y’all. You guys made the experience even better. Thank you the city of SA for welcoming me in with such open arms means a lot !		
Terrance Ross	Wait so Dune part 2 isn’t even green lit yet?	88.9	10
Jaylen Hoard	Emojis only	16.7	18
Draymond Green	Tshiebwe like TT on them O boards	22.2	14.3
Bismack Biyombo	Was about 8 & now it’s all about 18! We try to explain & they never understand the journey we on. You’re watching from above & all you have to do is just smile! All your life was about us & others. Now we are doing it for you by Gods Grace will get it done	71.4	17.3
Trendon Watford	Best game of the tournament so far	50	15.8

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