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All I do is win, win, win no matter what? Pre-game anxiety and experience predict athletic performance in the NBA

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ABSTRACT

In this study, we examine the relationship between anxiety and athletic performance, measuring pre-game anxiety in a corpus of 12,228 tweets of 81 National Basketball Association (NBA) players using an anxiety inference algorithm, and match this data with certified NBA individual player game performance data. We found a positive relationship between pre-game anxiety and athletic performance, which was moderated by both player experience and minutes played on the court. This paper serves to demonstrate the use case for using machine learning to label publicly available micro-blogs of players which can be used to form important discrete emotions, such as pre-game anxiety, which in turn can predict athletic performance in elite sports. Based on the results, we discuss these findings and outline recommendations for athletes, teams, team leaders, coaches, and managers.

1. Introduction

In the crucible of professional sports, where milliseconds decide outcomes and the smallest misstep can spell disaster, the complex interplay of psychological and physiological factors can dictate the trajectory of an entire career. At the epicenter of this interplay is anxiety—a multifaceted emotion that straddles both the psychological and physiological realms and has the potential to significantly influence performance outcomes (Sadler & Miller, 2010). Characterized by feelings of apprehension, tension, and a heightened state of physiological arousal, anxiety is as much an intrinsic part of elite sports as the athletes themselves (Cheng & McCarthy, 2018; Dunn & Schweitzer, 2005). The National Basketball Association (NBA), a global stage of unparalleled sporting prowess, amplifies the significance of this emotion like no other. Within this intensely competitive environment, players are persistently subjected to uncertain and high-stakes situations that can induce powerful feelings of anxiety. If these feelings become overpowering, they can cause players to "choke" under pressure, adversely affecting their performance (Craft et al., 2003). Given the high stakes, the relationship between anxiety and sports performance has been, and continues to be, a central focus of scientific investigation (Jones & Swain, 1995).

Nonetheless, the results elucidating the link between anxiety and athletic performance have been somewhat inconsistent regarding both the magnitude and direction of the effect (Kleine, 1990b). Some studies suggest a linear negative relationship between anxiety and performance, while others posit a curvilinear relationship, implying that a certain degree of anxiety can enhance performance, but an excess can be detrimental (Burton & Naylor, 1997; Gould et al., 2002; Krane, 1993). Furthermore, other research underscores the role of several moderating variables, including individual factors (e.g., self-confidence), task (i.e., type of sport), and situational characteristics (Mellalieu et al., 2006).

Although these studies have illuminated facets of the intricate relationship between anxiety and athletic performance, many previous research endeavors have been constrained by limitations. These include small sample sizes in terms of participant numbers and considered events (i.e., competitions), and the combination and comparison of athletic performance across various sports and competition levels (e.g., junior leagues, national level, international level).

In a bid to refine our understanding of the anxiety-performance relationship, we analyze pre-game anxiety among 81 NBA players, using an anxiety inference machine learning algorithm applied to a dataset of 12,228 tweets. This data is matched with official NBA individual player game performance statistics, serving as a demonstration of the predictive potential of pre-game anxiety for athletic performance. Crucially, this study also examines the moderating role of player experience and on-court time, factors we argue can significantly influence the relationship between pre-competition anxiety and performance outcomes. We hypothesize that that more experienced players may frame anxiety as a performance enhancer rather than a stumbling block, and hence outperform their less experienced counterparts at similar competitive levels. To

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examine this moderated relationship, the study harnesses multilevel discontinuous growth models, taking into consideration temporal aspects and the characteristics of players, teams, and opposing teams.

1.1. Anxiety in elite sports

State anxiety (often simply referred to as anxiety) is defined as negative valence, high arousal, and cognitive appraisals of uncertainty and low control (Dunn & Schweitzer, 2005). Anxiety can be differentiated from other ill-being proxies, such as negative affect (Cheng & McCarthy, 2018), in that it is a discrete emotion and does not involve multiple aversive emotional states such as affect. Furthermore, anxiety, and more specifically, state anxiety, is conceptualized as a transient event-specific emotional response usually triggered by a threat, such as an uncertain situation (Gruda & Hasan, 2019; Gruda, Ojo, et al., 2022; Gruda et al., 2023).

We argue that anxiety is a particularly interesting emotion to examine in the context of sports performance due to its possible impact on psychological and endocrinological well-being even before a competition (Salvador et al., 2003). For example, an anticipatory cortisol response is found before a stressful event such as a sports competition (Filaire et al., 2001). And while pre-competition anxiety affects all athletes, athletes seem to differ in their interpretation of these feelings as either debilitative or facilitative (Jones & Swain, 1995). One key differentiator is experience.

Previous research has indicated that both ability and skill level, elite vs. club or junior athletes (Kleine, 1990a), and self-confidence (Hanton et al., 2004) are key predictors of sports performance. For example, Kleine (1990a) found that a negative relationship between anxiety and sports performance was much more prevalent among athletes competing at a lower skill level than among elite athletes. Hence, experience could help distinguish between athletes who interpret pre-competition anxiety as negative (debilitative) or positive (facilitative), regardless of the sport type.

In addition, athletes who were confident in their abilities were more capable in controling themselves and their environments. One explanation might be that elite athletes endure increased pressure to perform compared to non-elite athletes, and grow accustommed to withstanding that pressure. Interestingly, some previous research suggests that some athletes seem “to have predispositions to interpret anxiety levels differently” (Jones & Swain, 1995) with elite athletes much more likely to interpreting pre-game state anxiety as facilitative rather than debilitative (Woodman & Hardy, 2003).

Taken together, the evidence thus far suggests that the effects of self-confidence on performance are clearer in elite athletes (Woodman & Hardy, 2003). In short, it stands to reason that a high skill level paired with a high degree of self-confidence can positively moderate the relationship between anxiety and sports performance.

1.2. Overview of the present study

Most previous research focused on convenience samples of athletes across sports types, as well as skill levels. Specifically, there is a lack of studies focusing on the link between discrete emotional anxiety in elite athletes, instead of merely positive or negative affect (Gruettner et al., 2020) or mood (Xu & Yu, 2015). The present study makes the first step in this direction by using a machine learning approach to infer the expression of anxiety in athletes' social media posts on Twitter pre-game day performance.

We examined data derived from Twitter to infer anxiety scores based on the expression of anxiety in athletes' tweets. Twitter has over 330 million monthly active users (statista.com), with an average of 6,000 tweets (up to 280-character text messages) posted per second. Twitter users' news feed captures their thoughts, feelings, and conversations at any moment in time, as microblogs are quick, short, and mostly capture what is going on at any particular moment in their lives (Gruda & Hasan, 2019). Indeed, Twitter data have been used extensively across disciplines to infer both traits (Gruda, Karanatsiou, et al., 2022) and state-like variables such as state anxiety (Gruda & Ojo, 2022).

Twitter data have also been used to infer the predictors of sports performance. For example, Jones et al. (2019) used athletes' Twitter posts to determine whether late-night tweeting was negatively associated with next-day game performance in a sample of NBA basketball players compared to non-late-night tweeting. They also observed that a higher frequency of late-night tweets was associated with less time played per player per game as well as a reduction in turnovers and personal fouls. Similarly, based on sentiment analysis of NBA player Twitter data, Xu and Yu (2015) found that athletes' tweets could be used as a proxy for their pre-match mood to predict game-day on-court performance. These results suggest that athletes' Twitter data might be equally used to infer state anxiety levels per tweet over an extended period, for example, during the entire sports season.

We chose to focus on basketball as our reference sport. This is because basketball demands both excellent fine motor skills and gross motor activity, which distinguishes it from other sports that are more heavily focused on one (e.g., gymnastics) or the other (e.g., sprinting). In addition, basketball is the 3rd most popular sport worldwide (after football/soccer and crickets) watched by over 2.5 billion people worldwide. The NBA alone is the third-highest-grossing league in North America with a revenue of $7.4 billion and regularly features attendance rates of 22 million in-stadium viewers per season (Mathewson, 2019). For this study, we considered all NBA players to be elite athletes because out of all college athletes who try out for the NBA, only 0.03% are selected to play at the NBA level. In other words, out of 10,000 male high school basketball players at any point in time (Williams, 2018), only three make it to the NBA.

2. Method

Linguistic-based text analytics (linguistic analytics) entails exploiting knowledge about a language, such as its syntax, semantics, and lexicons, to extract valuable insights from the text. It includes the use of specific linguistic elements found in the text as part of the features to be used in the text-mining process. In this study, we inferred anxiety scores for individual players in our dataset, we applied a pre-trained predictive model developed by Gruda and Hasan (2019) on a pilot sample of 81 Twitter-verified NBA players who played in the regular 2021-2022 season, across a total of 82 games featuring a total of 454 athlete game performances. More information regarding the applied algorithm is provided in the Measures section.

2.1. Analytical process

Our method comprises a four-stage process. The first step involved extracting and curating the tweet dataset. The second step involved inferring the anxiety scores for each available player tweet in our dataset. The third step in our process involves generating daily anxiety scores per player based on available tweets and matching these daily anxiety player scores to existing seasonal statistics data from https://basketball.com. Finally, we conducted a longitudinal analysis of the association between anxiety and game day performance using the generated dataset.

2.1.1. Dataset preparation

This step comprises three tasks. The first task involved the extraction of tweets from 268 twitter-verified NBA players. This Twitter list outlines some of the best-known NBA players. The extraction of player tweets was restricted to the duration of the 2021-2022 season, which ran from October 19th, 2021, to April 10th, 2022. Second, we extracted all tweets posted during the regular season from the timelines of each available Twitter-verified player. This produced a dataset of 12,228 tweets from 81 players.

2.1.2. Inferring state anxiety scores

The state anxiety prediction algorithm developed by Gruda and Hasan (2019) was central to the second step of this methodology, which required the assignment of anxiety scores to the collected tweets. This algorithm was crafted using a machine learning model, trained on a dataset of manually rated tweets, with the aim of scoring perceived anxiety levels in tweets. The training set was composed of 600 tweets that were randomly selected from the initial collection of 10,510 tweets made by 10,386 users. This subset of tweets was then assessed by 604 US participants for perceived anxiety, with each participant rating approximately five tweets. This human-rated data then served as a learning base for the machine-learning model. To process the tweets in a manner that the machine learning model could understand and learn from, two types of features were extracted from each tweet. The first feature was a semantic embedding vector. This vector represented each word in the tweet as a 300-dimensional vector, taking into account the distribution and relationship between different words. In other words, it captured the contextual meaning of each word in the tweet, which can be critical in gauging the sentiment, or in this case, the anxiety level present in the tweet. The second type of feature was a term frequency vector. This vector recorded the frequency of each term, including emojis, in a tweet. It allowed the machine learning model to understand which words and symbols were used most frequently and thus potentially held the most significance. Finally, to predict anxiety scores, the researchers used an ensemble of two regression models, each corresponding to one of the two types of features mentioned above. Bayesian ridge regression provided the best fit among the tested models for this purpose. Each model independently estimated an anxiety score for a tweet, and the final anxiety score assigned to a tweet was calculated as the mean of the two model-predicted scores. This approach aimed to integrate the insights from both types of features, thereby creating a more accurate and holistic prediction of anxiety levels in the tweets.

2.1.3. Matching game day performance data with labeled anxiety in the tweet dataset

Next, we merged the game performance data with the daily player anxiety scores. Because we restricted the present pilot study to a single season (i.e., 2021-2022) and Twitter verified profiles, this led to a reduction of our sample to 81 players. Furthermore, of those players, not all had tweeted close enough to (i.e., a few days before) the game day. Our final sample was composed of 1,652 tweets by 47 players and 454 dyadic anxiety-gameday performance observations, which formed the base dataset.

2.2. Measurements

2.2.1. Athletic performance

We define performance as “the effectiveness with which [athletes] perform activities that contribute to predefined goals and outcomes” (in this case, sporting success). Individual athlete performance can be defined numerically in various ways, including the total points scored by a player. However, because game performance, as measured by points scored, can be largely dependent on player position, we used a different standardized measure of individual player performance, as outlined by Sonstroem and Bernardo (1982).

$$\begin{aligned}\text{Performance} = {} & (Free\ Throw\ \% + Field\ Goal\ \%) * (Points\ Scored \\ & + Total\ Rebounds + Assists + Steals) - Turnovers \\ & - Personal\ Fouls + 10\end{aligned}$$

As has been done in previous papers (Xu & Yu, 2015), we normalized this performance indicator because we were more interested in individual player differences than absolute values.

2.2.2. Pre-game anxiety

Pre-game anxiety is defined as tweets posted by players at least one day before an upcoming game. This was done to be able to examine time-lagged effects (see Results). Pre-game anxiety was coded using a developed anxiety detection algorithm based on the abbreviated format of the STAI (Marteau & Bekker, 1992) composed of 6 items on a four-point scale, with 1 = “Not at all” and 4 = “Very much” (Gruda & Hasan, 2019). A meta-analysis (Kleine, 1990b) found no difference in population effect size between sport-specific anxiety measures and more traditional general anxiety measures, such as the State-Trait Anxiety Inventory. An example of a player’s state anxiety score over time is shown in Fig. 1.

2.2.3. Player experience

We also account for player experience (measured in years). The longer an athlete has played on an elite level, the more likely they are to be confident in and trust their abilities.

2.2.4. Minutes played

The less time (in minutes) a player plays, the lower the likelihood that they will be able to contribute to the team’s success. Hence, the amount of time played on-court is a potentially important moderator, which we account for in our model as a moderator.

2.2.5. Control variables

We controlled for player age as a player-specific characteristic. In addition, because basketball is a team sport, team performance may also affect individual athletic performance. Therefore, we controlled for team and opponent strength using the respective team and opponent game scores as a proxy. We argue that team scores are more likely to be more salient and more specific for each game than other possible proxies, for example, team rank. That is because team rank, while it reflects similar information in an aggregated format as well, is a more global measure.

3. Results

Individual-level player game-day performance observations were nested within the teams. We controlled for the level of analysis to account for non-independent observations in our data. Hence, to estimate the association between state anxiety and sports performance, we fitted a multilevel discontinuous growth regression model over time. All statistical analyses were conducted using Stata version 17.0. The zero-order correlations are shown in Table 1, and the main analyses are presented in Table 2.

As shown in Table 2, the main three-way interaction significantly predicted athletic performance (b = .02, SE = .01, t = 2.70, p = .007). To better understand this interaction, we plotted the results (Fig. 2).

Graphing this interaction (Fig. 2) yielded two key findings. First, player experience matters greatly in how pregame anxiety is interpreted. For example, while a low degree of pre-game anxiety seems to be more facilitative to a less experienced player (low anxiety, experience 4 years: slope = .06, SE = .02, $z = 2.33$, $p = .02$), high pre-game anxiety seems to result in increased performance in more experienced players (high anxiety, 10 years experience: slope = .15, SE = .02, $z = 6.57$, $p < .001$) the longer players are on-court. In addition, in the case of very experienced players (i.e., 10 years), even average levels of pre-game anxiety seem to be positively associated with athletic performance (average pregame anxiety: slope = .08, SE = .01, $z = 10.41$, $p < .001$), however, the strongest positive effect on performance is predicted by high pre-game anxiety (as described above, slope = .15, $p < .001$). Second, this effect is more pronounced the longer players played in any respective game.

3.1. Multiverse robustness check

We note that in Fig. 2, the results shown are restricted to posted tweets up to three days before a respective game. While most tweets were indeed posted the day before the game, sometimes a player’s last pre-game tweet was two, three, or more days before a respective game. Some players do not play every single game; hence, there would be a

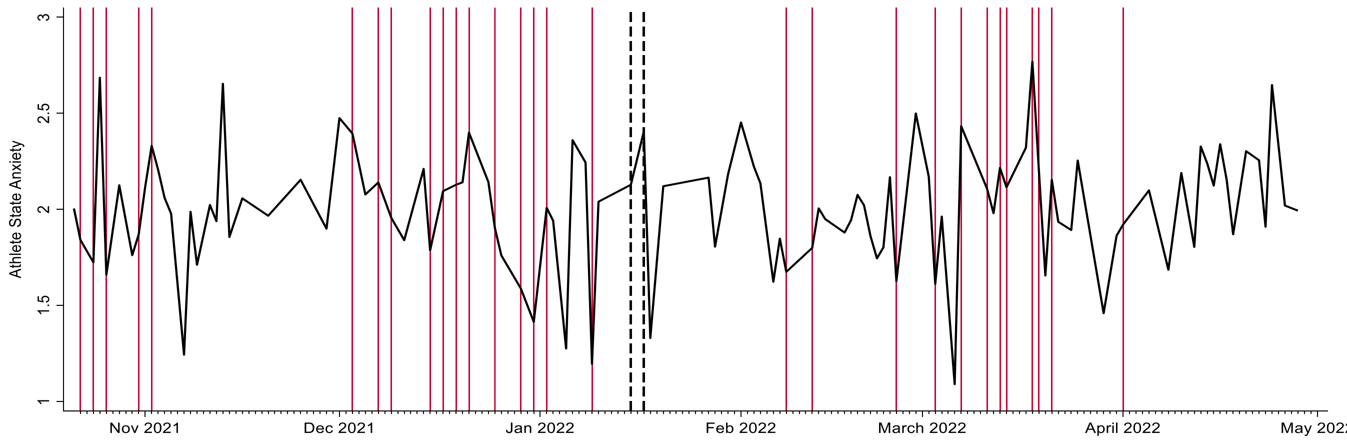

Fig. 1. Random player's anxiety over time.
Note: Anxiety over time = black horizontal line, game days = red vertical lines.

Table 1
Zero-order pairwise correlations of main variables.

		M	SD	1	2	3	4	5	6
1	PERF	0	1						
2	PG ANX	2,12	0.34	0.02					
3	EXP	7.05	1.56	.22***	-0.03				
4	MP	24.18	11.92	.68***	-0.03	0.07			
5	Age	26.59	1.34	-0.01	-0.04	.69***	-.12**		
6	T-Score	111.82	12.65	.18***	0.01	0.04	0.05	0.04	
7	O-Score	110.46	11.91	-0.06	-0.06	0.08	-0.07	0.01	.19***

Note: PERF = Performance, PG ANX = Pre-Game Anxiety, EXP = Experience, MP = Minutes played, T = Team, O = Opponent Team; *** $p < .001$, ** $p < .01$; n = 454.

Table 2
Main analyses.

	b	SE	t	[95% CI]
Experience	.88**	0.31	2.86	[.28, 1.48]
Minutes Played	0.2	0.1	1.94	[-.02, .39]
Pre-Game Anxiety	2.30*	1.13	2.04	[-.09, 4.52]
Experience X Minutes Played	-.03*	0.01	-2.06	[-.05, -.00]
Experience X Pre-Game Anxiety	-.41**	0.15	-2.7	[-.71, -.11]
Minutes Played X Pre-Game Anxiety	-.09*	0.05	-2.02	[-.18, -.00]
Experience X Minutes Played X Pre-Game Anxiety	.02*	0.01	2.7	[.00, .03]
Age	-.17**	0.06	-3	[-.28, -.06]
Team Score	.01**	0.00	3.07	[.00, 0.02]
Opponent Score	-.01**	0.00	-3.03	[-.02, -.00]
Time	0.00	0.00	0.73	[-.00, .00]
Constant	-18.76	22.08	-0.85	[-62.04, 24.52]

Note: Time = date; ** $p < .01$; n = 267.

longer time gap between tweets and game-day performance. Hence, to provide transparency regarding the consequences of our pre-processing decisions on our results, we conducted and present a multiverse analysis, as suggested by (Steegen et al., 2016), which extends the number of pre-game tweets up to 3-10 days before the game day (Fig. 3).

Whenever a researcher works with available data, each data preparation decision effectively creates an alternate universe in which this decision is not taken, or a different decision is taken instead. Hence, in a multiverse analysis, analyses are rerun for each created sub-dataset. In our case, this meant rerunning our multilevel model for each sub-dataset created due to the restriction of considered tweet days before a respective game. This allowed us to determine and document which results are robust across pre-processing options (Gruda et al., 2022; Steegen et al., 2016).

The results of our multiverse analysis were interpreted consistently using a random effects model (Hamaker & Muthén, 2020). In a fixed-effects model, all multiverses are assumed to be drawn by the same population, whereas in a random-effects model, the various multiverses are assumed to be drawn from different populations. We summarize our multiverse analysis results in Fig. 3, which outlines the respective interaction coefficients across all the considered multiverses.

The robustness check results (Fig. 3) indicate that the respective three-way interaction coefficients across all examined multiverses have the same (positive) sign across all multiverses, and are significantly different from zero in all multiverses. This indicates that the examined interaction result is robust and unlikely to be due to the data-preparation process.

4. Discussion

This study offers a compelling demonstration of how machine learning-based text analytics can illuminate the complex relationship between pre-game anxiety and athletic performance, particularly in high-stakes environments like the NBA. Leveraging this innovative approach

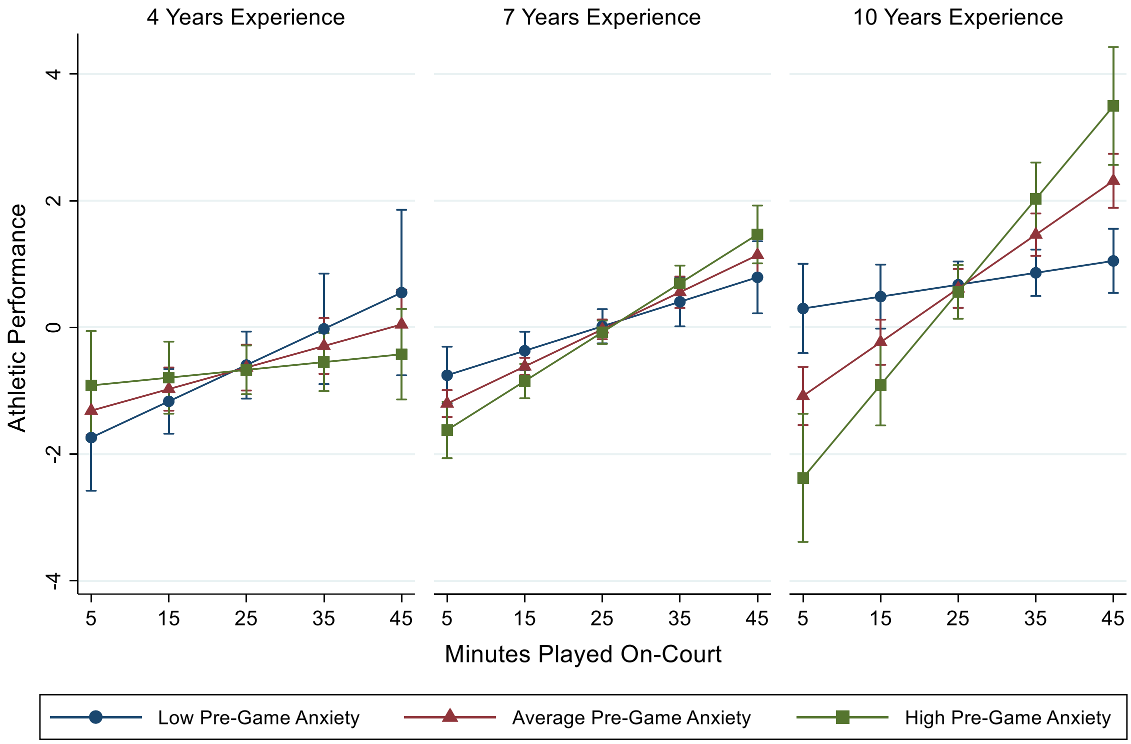

Fig. 2. Interaction between pre-game anxiety, experience, and minutes played predicting athletic performance.
Note: Pre-game anxiety graphed at 1st, 50th, and 99th percentile; pre-game anxiety was limited to up to three days before game day, n = 267 observations.

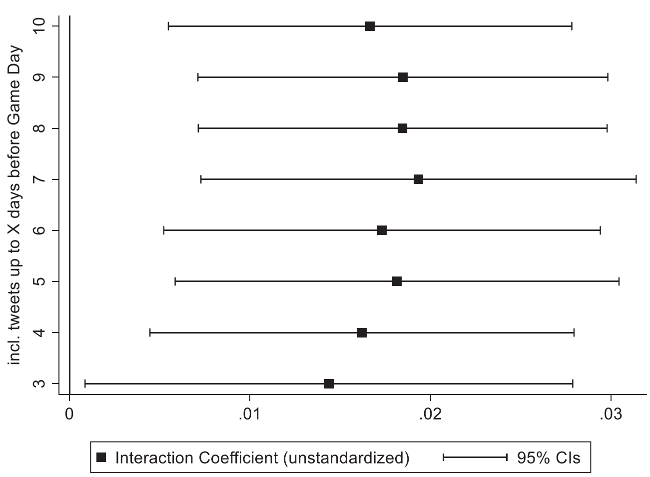

Fig. 3. Multiverse robustness check results.

enables us to link non-intrusive data collection from social media platforms with an examination of performance patterns at both the individual and broader sports population levels over time (Xu & Yu, 2015). Tweets posted by players are public, abundant, and provide an easily accessible window into their emotional states prior to games.

While text analytics proves a powerful tool, previous research efforts examining sports performance with similar methods have largely centered on broader emotional constructs, such as positive versus negative affect (Gruettner et al., 2020), or general mood (Xu & Yu, 2015). In contrast, our study drills down into a specific emotion—anxiety, a much-discussed yet complex factor in sports performance.

Our findings indicate a positive relationship between pre-game anxiety and performance in NBA athletes. However, two crucial moderating factors—player experience and game duration—significantly shape this relationship. In essence, player experience seems to transform the impact of anxiety from potentially detrimental (in less experienced players) to beneficial (in more seasoned players). It is noteworthy that players with moderate experience (for instance, 5 years) showed little to no performance variance due to anxiety. This finding holds important implications for coaches and managers, who must consider a player's experience level when deciding on their game time.

Another contribution of this study is that we performed multiverse analyses to understand the robustness of our results. Our multiverse analysis examined the extent to which our conclusions were limited by the number of days the last pre-game tweets were posted, which in turn formed the basis upon which pre-game anxiety was measured. For example, it could be that the closer to the game the pre-game anxiety is derived from, the more predictive the relationship between the main three-way interaction and athletic performance. However, we did not find any evidence for this. Instead, the presented multiverse robustness check showed that the results remained robust even when considering a broader definition of pre-game anxiety (e.g., including the last pre-game tweets posted up to four, five, or seven days before the game).

4.1. Implications

The findings of this study offer several practical implications for athletes and coaching staff in the realm of professional basketball and potentially extend to other elite sports contexts.

4.1.1. Tailored player management strategies

The differential impact of pre-game anxiety based on player experience underscores the need for individualized management strategies. Coaches could refine their pre-game routines and motivational talks to align with each player's experience level and anxiety interpretation, thus fostering optimal performance.

4.1.2. Mentorship programs

Experienced players can share their strategies for harnessing anxiety in a facilitative manner with less experienced teammates. This exchange of strategies could be formalized into mentorship programs within teams, enhancing the skillset of athletes new to high-pressure environments.

4.1.3. Informed coaching decisions

Coaches, with a deeper understanding of how player experience and anxiety interact, can make more informed decisions regarding player time allocation during games. These decisions could not only maximize individual performance but also potentially shape the overall team's performance.

4.1.4. Promoting mental health

By illuminating the relevance of pre-game anxiety in performance, this study also advocates for the importance of mental health in sports. Open discussions and supportive management of anxiety can lead to the reduction of associated stigma, creating a healthier sports culture.

4.1.5. Data-driven psychological interventions

The demonstrated potential of pre-game anxiety as a predictor for performance could inform the design of data-driven psychological interventions. These interventions could aim to provide athletes with personalized anxiety management techniques, further enhancing performance outcomes.

While these practical implications provide a promising starting point, individual adaptation remains paramount, recognizing that optimal strategies can vary among athletes due to a host of individual and situational factors.

4.2. Limitations and future research

The present study is not without limitations. First, we acknowledge that the presented analysis and findings are based on a small sample of NBA players. This study served to demonstrate and better understand how various game-related variables interact with pre-game anxiety to predict athletic performance.

Moreover, our analysis was confined to male athletes in the NBA. This is a significant limitation given that previous research suggests differences in anxiety experiences between male and female athletes (Anshel & Sutarso, 2007; Kleine, 1990b). Female athletes often report higher levels of pre-competition anxiety, but it remains unclear whether they interpret anxiety as more of a hindrance or an aid compared to their male counterparts. Thus, comparative analysis involving both NBA and WNBA athletes could yield insightful results, particularly when considering similar competitive environments at the national level.

5. Conclusion

In summary, we contribute to the existing literature on the complex relationship between pre-game anxiety and athletic performance by providing additional insights into important moderators. In addition, we used a case for using machine learning-based text analytics to label publicly available microblogs of players, which can be used to form important discrete emotion predictors such as pre-game anxiety. These data, in turn, can predict athletic performance when considered in a larger framework of other important moderators, including player experience and minutes played.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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