Final Project – Running Hot: Determining the probability of injuries

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MSDS 356 Winter 2023

Northwestern University, Sports Performance Analytics

03/07/2022

Introduction

The idea of load management in the National Basketball Association (NBA) has become more common across the league and has been criticized for undermining the regular season's integrity as it leads to a negative effect on team performance and fan interest. Anthony Edwards of the Minnesota Timberwolves said, "Just play man. If you 70-80 percent, you got to play. I don't like all the sitting out and missing games…these people might have enough money to come out to one game and you sitting out [sic]" (Sunjic 2023). However, former NBA player JJ Reddick explained on an episode of his podcast, *The Old Man & the Three*, that it is not always on the players to decide whether they will sit out. "A lot of times, there's a performance team, and they have all these different metrics measuring you on a weekly basis, and they call it 'running hot.' They will legitimately give you a heads up, and say, 'Hey, all your data says you're running hot. You may need to sit out next week. Which game looks better for you?'" (Reddick 2022).

This study analyzes historical data to determine key indicators that provide insight into when a player should sit out. The data analyzed is focused on physical attributes and on-court activity since such factors tend to contribute toward injuries, according to previous studies. Along with the variables based on activity and physical attributes, week-to-week metrics are also taken into consideration in order to determine the likelihood of a player "running hot" and facing an injury over the course of a season. A logistic regression model was then created to predict the probability of a player missing the next game. The accuracy, precision, recall, and F1 score were analyzed to determine the reliability of the model. Ultimately, the study focuses on providing a model that can be used by players and teams to determine the likeliness of a player sitting out, and through such analysis, organizations and individuals can take the proper steps to avoid injuries while "running hot."

Literature review

A study from the *Journal of Data Analysis and Information Processing* stated that "the injury plays a vital influence in an NBA match and it may reverse the result of two teams with wide strength disparity." The article suggests a pipeline to predict injuries in NBA games using player and team data. However, due to limited and unbalanced data, the prediction power was limited. Results showed that a player's own performance is the most significant factor in their injury, and Principal Component Analysis (PCA) was applied to help reduce the dimension of the data and to show the correlation of different features (Wangwei 2020). Like this study, the data used in this report is based on on-court activity, and those variables are used as predictors to determine whether a player will sit out the next game.

According to a study focused on driving to the basket, players depend on acceleration, deceleration, and lateral movements when driving to the basket. The study analyzed NBA seasons from 1980 to 2017 to investigate the relationship between players' tendency to drive and their likelihood of tearing their anterior cruciate ligament (ACL), as well as their performance on returning to play after ACL reconstruction. Results showed that players with a higher career-average drive tendency were more likely to tear their ACL, but there was no significant difference in performance between cases and controls after returning to play. The study suggests that this information can be used to target players with certain playing styles for ACL injury prevention programs (Schultz, Blake J. 2021). Similarly, this report accounts for data that is heavily focused on physical activity like usage rate, as well as physical attributes such as height and weight, to determine the likelihood of the player sitting out.

Concepts like machine learning, and more specifically deep learning, are utilized in sports injury analysis in order to predict injury risks. A deep learning approach, METIC, was used in a research study to classify injuries based on past injuries and game activity. Much like variables considered in the deep learning study, this report also takes into account historical injury reports and game activity to determine if a player is running hot and will likely miss a game due to an injury or rest. The METIC model was able to achieve high-level prediction and provided useful insights into non-linear relationships among player activity and history. METIC captured complex non-linear relationships among multiple data points by using representational learning that provides a robust generalization of sports injuries. According to the study, the model can be used by athletes and sports organizations to stratify injury risk and inform athlete management decisions to mitigate injury incidence and improve performance (Cohen, Schuster and Fernandez 2021). The suggestion is similar to the concept of running hot that JJ Reddick speaks about on his podcast.

NBA players face a high chance of never being the same player they were before a major injury. A study from the *Asia-Pacific Journal of Sport Medicine, Arthroscopy, Rehabilitation and Technology* analyzes the prognosis of elite basketball players after an Achilles tendon rupture. The aim of the study was to quantify the impact of Achilles tendon rupture on the post-injury performance of basketball players and explore the correlation between recovery timeline and pre-injury characteristics. Data was collected for 12 players who met the inclusion criteria and compared their Player Efficiency Ratings (PER) with matched controls based on PER, age, and playing position. The results showed that two players failed to return to playing professionally and others took an average of 10 months to return to play. On average, it took about 1.8 seasons to reach their post-injury peak performance level. The post-injury peak performance was significantly worse than the pre-injury level but similar to matched non-injured players. The study concluded that Achilles tendon rupture can be a career-ending injury for professional basketball players. Age is a factor that is also considered in this report, and similar to this study, height instead of position is also considered in this report to determine the probability of players missing games.

Methods

Based on the literature review, the data collected for this study focused on the physical attributes of players and the on-court activity that would likely contribute towards "running hot," which is the concept of facing a possible injury in the near future. Data was collected for 106 players from the 2021-22 NBA season by filtering for an average playing time of 27 minutes or more. Most players with this many minutes would include many starters and key players off the bench. Data was sourced from NBA.com and consisted of features such as shots attempts and makes, free throw attempts and makes, assists, steals, and blocks, as well as advanced statistics like usage rate, points in the paint area, point in the midrange area. That information was collected for every game a player participated in during the season, so if a player played in all 82 regular season games, there would be 82 rows for the player. Player bio data such as age, weight, and inches were scraped from NBA.com as well since these attributes could possibly play a part in determining injury for the next game. Other game data that was calculated consisted of total statistics from the previous week of games from the game log game date, such as the number of games played, shot attempts and makes, turnovers, blocks, and personal fouls. From Pro Sports Transactions, injury data was collected, including the date of the injury and return, the player and his team, and notes associated with that injury. Team schedule data for the 2021-22 NBA regular season was procured using the nbastatR::seasons_schedule() API available in the R programming language library, which was used to merge player game log with the injury list and missed games datasets. The full list of game log variables used for modeling are listed below:

Table 1. Game Log Variables

Variable	Definition
MIN	Minutes Played - The number of minutes played by a player
FGA	Field Goals Attempted - The number of field goals that a player has attempted. This includes both 2 pointers and 3 pointers
FG3A	3-Point Field Goals Attempted- The number of 3-point field goals that a player has attempted
FTA	Free Throws Attempted - The number of free throws that a player has attempted
OREB	Offensive Rebounds - The number of rebounds a player has collected while they were on offense
DREB	Defensive Rebounds - The number of rebounds a player has collected while they were on defense
AST	Assists - The number of assists – passes that lead directly to a made basket – by a player
TOV	Turnovers - A turnover occurs when the player on offense loses the ball to the defense
STL	Steals - Number of times a defensive player takes the ball from a player on offense, causing a turnover
BLK	Blocks - A block occurs when an offensive player attempts a shot, and the defense player tips the ball, blocking their chance to score
PF	Personal Fouls - The number of personal fouls a player committed
PFD	Personal Fouls Drawn - The number of personal fouls that are drawn by a player

USG_PCT	Usage Percentage - The percentage of team plays used by a player when they are on the floor
PIE	Player Impact Estimate - PIE measures a player's overall statistical contribution against the total statistics in games they play in. PIE yields results which are comparable to other advanced statistics (e.g. PER)
POSS	Possessions - The number of possessions played by a player
AGE	Age - The age of a player
PLAYER_HEIGHT_INCHES	Player Height in Inches - The height of a player in measured in inches
PLAYER_WEIGHT	Player Weight - The weight of a player
FGM_PAINT	Field Goals Made in the Paint - The number of field goals made in the paint
FGM_2PT_MR	The number of mid-range 2-point field goals made
PW_MIN	Minutes Played in the Past Week - The number of minutes played by a player in the past week
PW_GAMES	Games in the Past Week - The number of games a player or team played in the past week
PW_FG3A	3-Point Field Goals Attempted in the Past Week - The number of 3-point field goals that a player has attempted in the past week
PW_FG2A	2-Point Field Goals Attempted in the Past Week - The number of 3-point field goals that a player has attempted in the past week
PW_OREB	Offensive Rebounds in the Past Week - The number of rebounds a player has collected while they were on offense in the past week
PW_DREB	Defensive Rebounds in the Past Week - The number of rebounds a player has collected while they were on defense in the past week
PW_ASTS	Assists in the Past Week - The number of assists by a player in the past week
PW_TOV	Turnovers in the Past Week - The number of turnovers by a player in the past week

PW_STL	Steals in the Past Week - The number of steals by a player in the past week
PW_BLK	Blocks in the Past Week - A block occurs when an offensive player attempts a shot, and the defense player tips the ball, blocking their chance to score
PW_POS	Possessions in the Past Week - The number of possessions played by a player in the past week
PW_PF	Personal Fouls in the Past Week - The number of personal fouls a player committed in the past week
PW_PFD	Personal Fouls Drawn in the Past Week - The number of personal fouls that are drawn by a player in the past week
PW_FGM_PAINT	Possessions in the Past Week - The number of 2-point field goals made by a player in the past week
PW_FGM_2PT_MR	2-point mid-range field goals made in the past week - The number of 2-point mid-range field goals made by a player in the past week
PW_PIE_AVG	Average Player Impact Estimate (PIE) in the Past week - The average PIE by a player in the past week
PW_USG_PCT_AVG	Average Usage Percentage Rating in the Past Week - The average user percentage rating by a player in the past week
CAREER_INJURIES	Career Injuries - The number of career injuries accumulated by a player up to the game date
DAYS_LAST_INJURY	Days Last Injury - The number of days since a player's last career injury up to the game date
OUT_NEXT_GAME	Out Next Game - Indicator (0=false, 1=true) that the player sits out the next game in the team schedule (dependent variable)

Soure: NBA.com, retrieved February 15, 2023.

The CAREER_INJURIES variable is based on the number of listings from the Pro Sports Transactions injured list and missed games datasets for a player listed on the website that is marked as "Acquired." The DAY_LAST_INJURY variable is based on the difference of days between the last date on the Pro Sports Transactions injured list and missed games datasets for a player listed on the website that is marked as “Acquired” and the game date of a game log.

The dependent variable is the OUT_NEXT_GAME variable, a flag (0 = false, 1 = true) on a game log that indicated the player on the game log will not be playing the next regular season game for their team due to injury based on the Pro Sports Transactions injured list and missed games datasets for the game log game date and player. As a dependent variable, the calculated probability of OUT_NEXT_GAME is used as the “Running Hot Index” for the decision engine that uses the model to evaluate the risk of injury of a player playing the next game in the regular season in a 0-to-1 scale, with 0 indicating no risk and 1 indicating 100% risk or fully “running hot.”

During the data collection process, it became difficult to procure the game log and injury data from NBA.com and Pro Sports Transactions respectively. Due to technical limitations and time constraints a limited amount of data was collected, resulting in the complete regular season game logs and injury data of 106 players in the 2021-22 NBA regular season who averaged more than 27 minutes per game (MPG). Setting the MPG to 27 provided over 100 players in order to develop a model with a reliable proof of concept.

One technical difficulty that was not resolved due to time constraints was merging player game log and injury history data for players who were traded during the 2021-22 regular season. An example of such a player is 10-time All-Star James Harden, who averaged 36.8.minutes per game in the 2021-22 season but was traded from the Brooklyn Nets to the Philadelphia 76ers. Thus his game logs from the 2021-22 season were not included in the resulting dataset.

Another difficulty not resolved was adding players that do not have previous injury history just prior to the 2021-22 regular season. This would include first year players (ie.

rookies) and those who have not yet experienced an injury in their career at that point. An example of a player would include the 2022 NBA Rookie of the year, Scottie Barnes of the Toronto Raptors, who averaged 35.4 minutes per game that season. Due to the technical limitation, his game logs were not included in the dataset.

Manually synching player names on NBA.com with injury list and missed games data on Pro Sports Transactions was another difficulty that was encountered, as some player names on the Pro Sports Transactions datasets include all aliases that include several variations of their name. An example would be Miami Heat center Bam Adebayo, who is listed as “Edrice Adebayo / Bam Adebayo” on Pro Sports Transactions. Due to time constraints, the names of 146 players who averaged more than 27 minutes in the 2021-22 regular were manually synced between the game logs, injury list, and missed games datasets.

Revisiting and resolving the technical debt described above in the future would result in a richer dataset to be used in fitting the model. It would also be ideal to include other NBA regular seasons of game log data as well when given the opportunity. Despite the issues, 6,699 game logs from over 100 players were gathered for the dataset from the 2021-22 NBA regular season.

An exploratory data analysis (EDA) was conducted on the dataset, which included an analysis of the correlation between the features and the dependent variable OUT_NEXT_GAME. The analysis shows that DAYS_LAST_INJURY has a very strong negative correlation to OUT_NEXT_GAME (-16 percent), which could have significant bias and overfitting when developing a predictive model. The next strongest correlation is CAREER_INJURES at 10 percent [Figure 1].

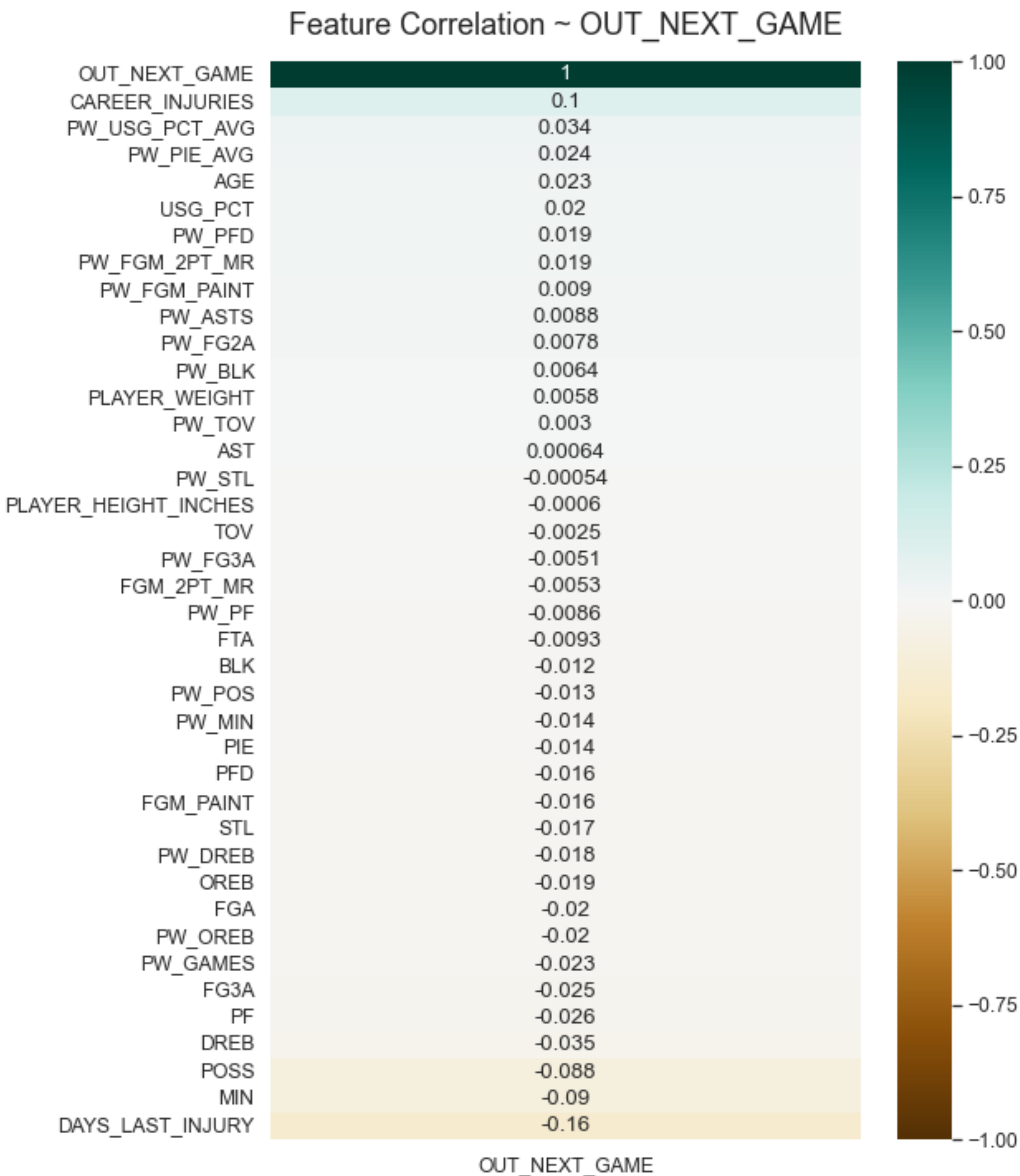

Figure 1. Feature Correlation to OUT_NEXT_GAME

Another observation from the EDA is the large disparity between OUT_NEXT_GAME values in which there are an overwhelming number of OUT_NEXT_GAME = 0 (false) game logs. That is expected since most players attempt to play as many games as possible throughout the regular season if they are healthy enough to do so. There were 6,182 rows with OUT_NEXT_GAME = 0 (92.28 percent) and 517 rows with OUT_NEXT_GAME = 1 (7.72 percent) in the game log training dataset [Figure 2]. To help resolve the disparity, oversampling was performed on the game log dataset to even the distribution between both values, but it was applied to the training dataset that was fitted to the model after an 80/20 percent train/test split.

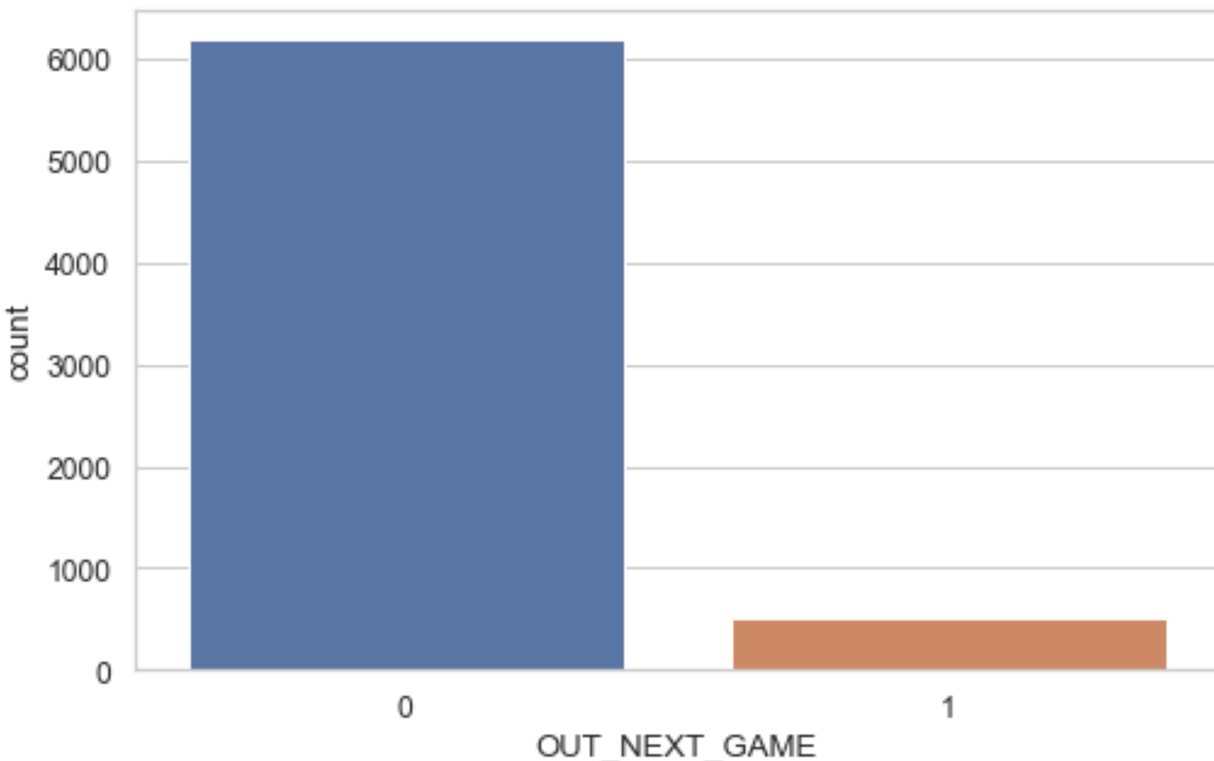

Figure 2. Count of OUT_NEXT_GAME values (0,1) in the game log dataset

Logistic regression is an ideal candidate to use for modeling as its results provide probabilities between a given set of possible classifications. In this case of the dependent variable, OUT_NEXT_GAME, there is a binary classification (0 = false, 1 = true) in which logistic regression would be appropriate to use. As standard practice for logistic regression, the oversampled training dataset was standardized by transformation using the scikit-learn StandardScaler() library in Python before fitting it to the model. After fitting the logistic regression model with the training dataset, the model's performance was evaluated based on accuracy, precision, recall, and F1 score using the test dataset.

The results show an accuracy of 93 percent and recall of 91 percent of the model predicting OUT_NEXT_GAME = 1 on the test dataset, but show a precision of 54 percent and F1-score of 68 percent. While the results indicate an overwhelming accuracy of the model predicting OUT_LAST_GAME = 0, the results seem mixed with predicting OUT_LAST_GAME = 1, shown by the 54% precision in the classification report [Table 2].

Table 2. Classification Report of Fitted Logistic Regression Model

	Precision	Recall	F1-Score	Support
0	0.99	0.94	0.96	1239
1	0.54	0.91	0.68	101
Accuracy			0.93	1340
Macro Avg	0.77	0.92	0.82	1340
Weighted Avg	0.96	0.93	0.94	1340

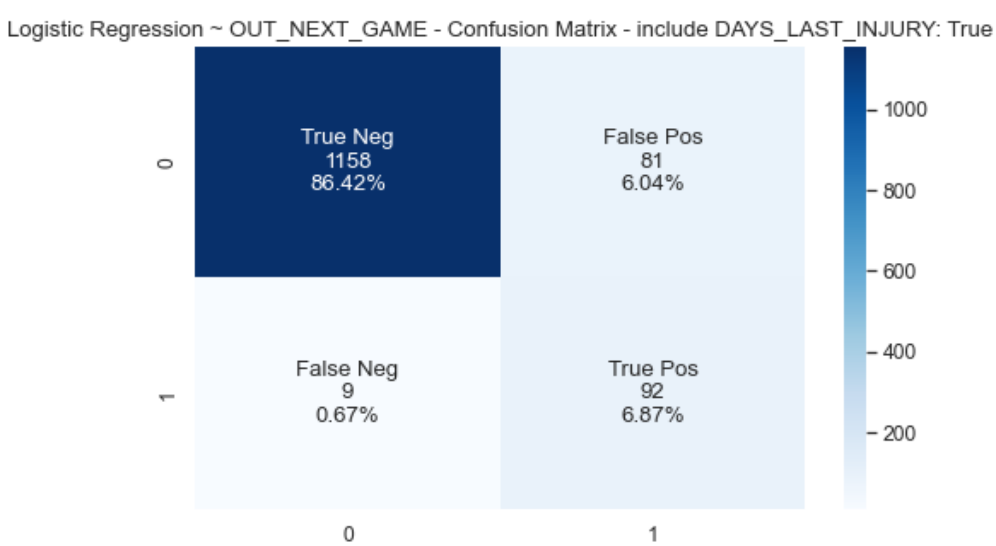

Figure 3. Confusion Matrix of Fitted Logistic Regression Model

Strong negative correlation of DAYS_LAST_INJUY [Figure 1] was an indicator to how much influence, and bias, it would have on the model [Figure 4].

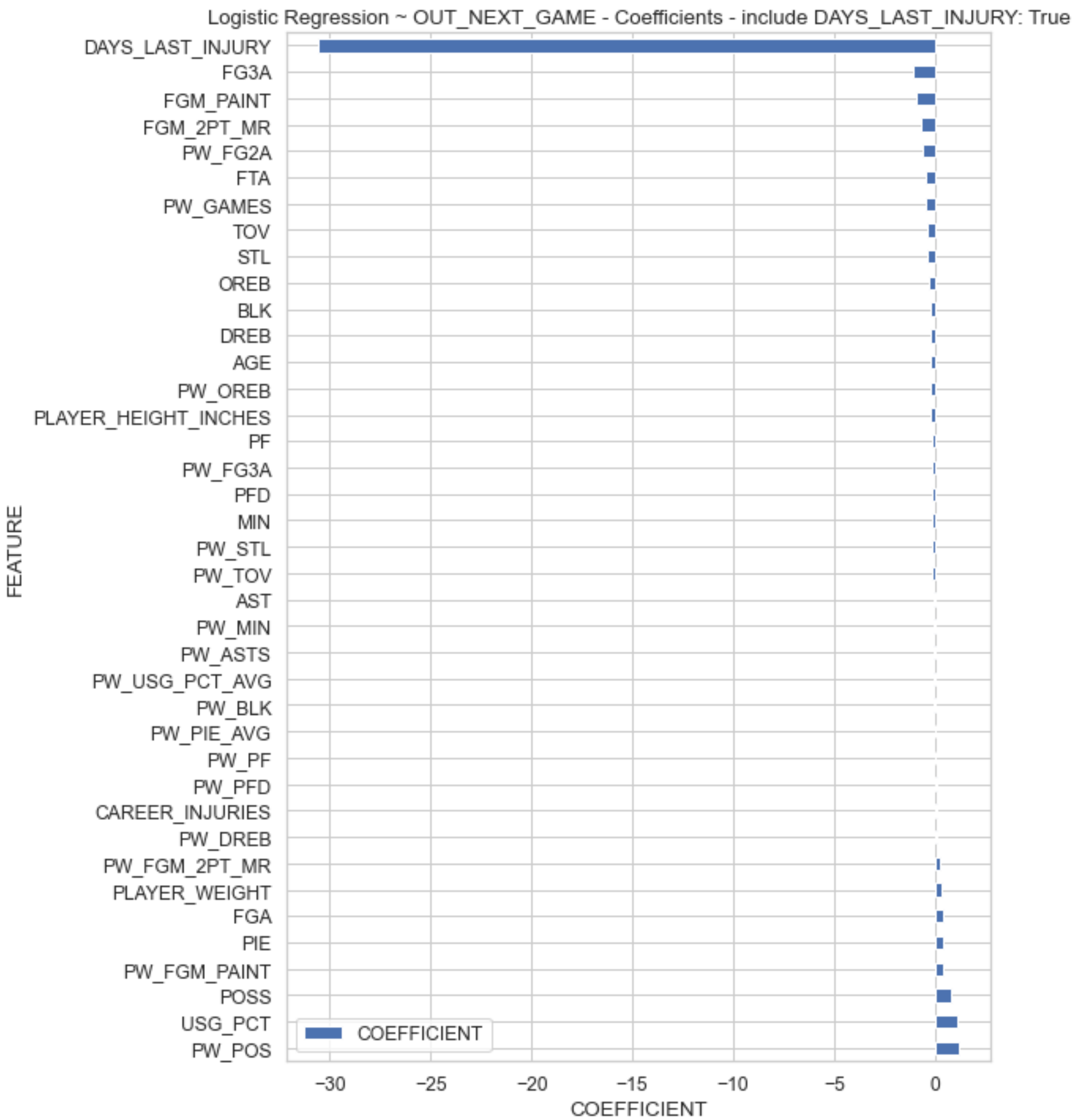

Figure 4. Coefficient Values for each Feature of Fitted Logistic Regression Model

As the fitted logistic regression model is a binary classifier, further model performance is observed with a Receiver Operator Characteristic (ROC) curve. The ROC curve displays very high rates of specificity/false-positive rate (FPR) and sensitivity/true-positive rate (TPR), along with a high area under the curve (AUC) of 97.6 percent [Figure 5]. This high performance of the model shown by this ROC curve could be due to potentially overfitting the training data and the bias of DAYS_LAST_INJURY.

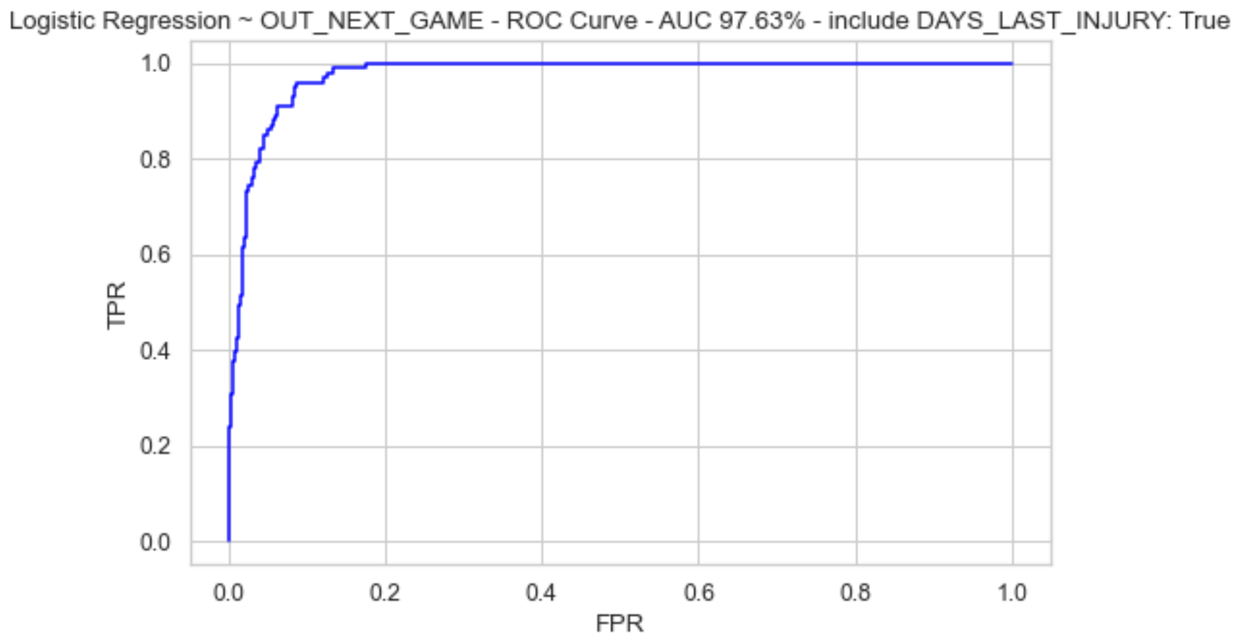

Figure 5. ROC Curve of Fitted Logistic Regression Model

To mitigate the heavy bias of DAYS_LAST_INJURY on the model, an alternate model without the feature was also created using the test dataset. Compared to the model using all features, results from the classification report show lower accuracy of 72 percent on the alternate model predicting OUT_NEXT_GAME = 1 on the test dataset, and an even lower recall of 33 percent, precision of 10 percent, and F1-score of 15 percent [Table 3].

Table 3. Classification Report of Logistic Regression Model without DAYS_LAST_INJURY

	Precision	Recall	F1-Score	Support
0	0.93	0.75	0.83	1239
1	0.10	0.33	0.15	101
Accuracy			0.72	1340
Macro Avg	0.52	0.54	0.49	1340
Weighted Avg	0.87	0.72	0.78	1340

The confusion matrix supports the very low precision of 10 percent in the classification report, showing the disparity between the number of false positive and true positive results [Figure 6].

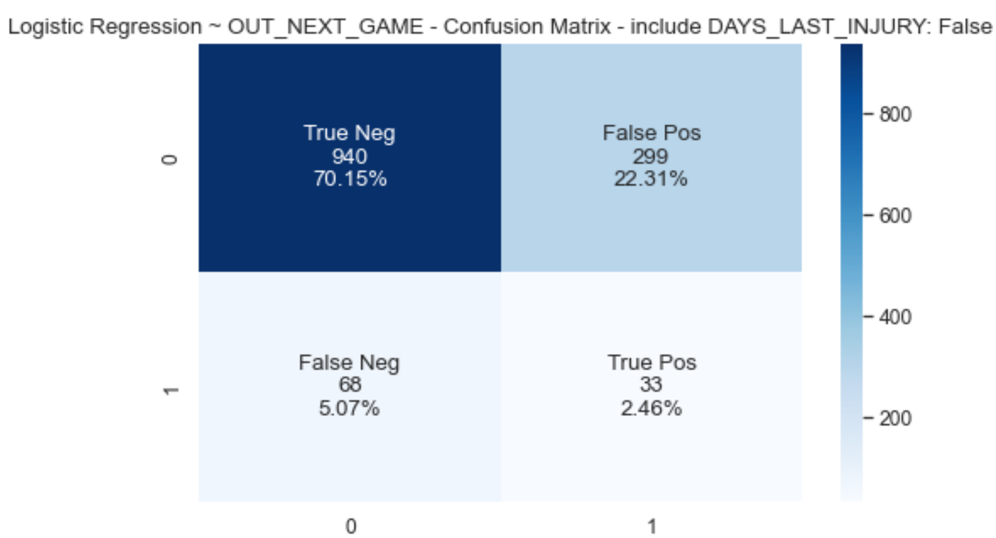

Figure 6. Confusion Matrix of Fitted Logistic Regression Model without DAYS_LAST_INJURY

The coefficients for each feature in the alternate model were also calculated. Without the bias of DAYS_LAST_INJURY, it can be seen that a broader distribution of coefficient values is used in the alternate model, but overall, however, the values are relatively low [Figure 7].

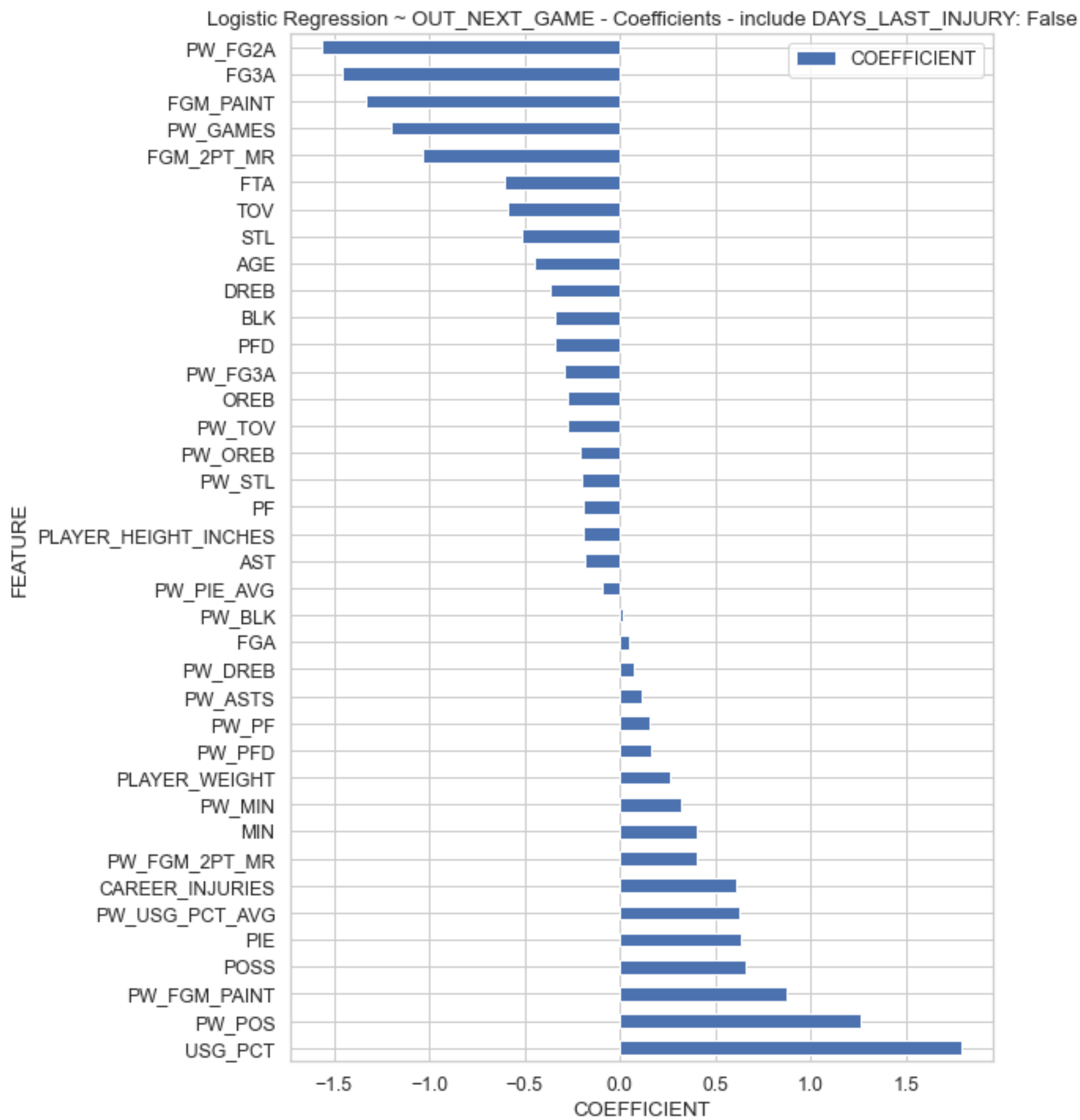

Figure 7. Coefficient Values for each Feature of Fitted Logistic Regression Model without DAYS_LAST_INJURY

The ROC curve of the alternate model shows very low FPR and TPR resulting in an almost-diagonal line with an AUC of 56.11 percent. Due to the low overall performance of the alternate model, the original model using all features was selected to be used in the development of the "Running Hot Engine" [Figure 8].

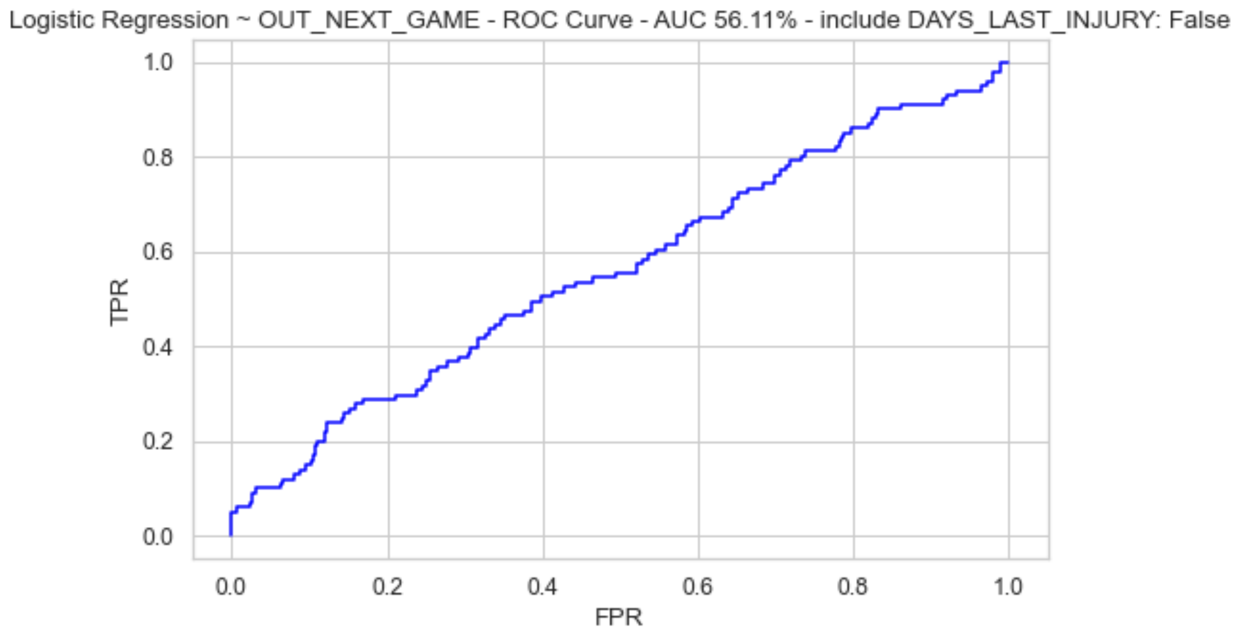

Figure 8. ROC Curve of Fitted Logistic Regression Model without DAYS_LAST_INJURY

Results

The fitted logistic regression model containing all features is the basis of the decision engine application. Called the “Running Hot Engine,” the decision engine is named after the term former NBA player JJ Reddick mentioned in several episodes of his podcast, *The Old Man & the Three*. He stated that a member of an NBA team’s performance staff would notify players that they are “running hot” based on metrics calculated using their performance data, and recommends that they sit out an upcoming game. While the specifics used behind these metrics are not publicly known, the Running Hot Engine aims to replicate that process. The decision ending uses the logistic regression model’s probability predictor to calculate a “Running Hot Index” (a value between 0 to 100) based on a player’s individual last game log data that consists of the features described in this study. Given a “Running Hot Threshold” value (also a value between 0 to 100), if the index exceeds the threshold value, the engine would indicate that a player is “running hot.” Using the Running Hot index, threshold, and indicator, the player, coaching and training staff can determine if the player should sit out the next game on their schedule.

For example, the Running Hot Engine can be fed the 2021-22 second-to-last regular season game log stats of Dallas Mavericks point guard Luka Doncic, along with additional statistics up to the game date such as his age, weight, height (in inches), number of career injuries, and number of days since their last career injury, and a subset of total or average statistics based on games played in the previous week (all required features for the Running Hot Engine are described in Table 1) [Figure 9].

SEASON_YEAR	2021-22	POSS	62
PLAYER_ID	1629029	PTS_PAINT	10
PLAYER_NAME	Luka Doncic	PCT_PTS_2PT_MR	0.0
TEAM_ID	1610612742	AGE	23
TEAM_ABBREVIATION	DAL	PLAYER_HEIGHT_INCHES	79
TEAM_NAME	Dallas Mavericks	PLAYER_WEIGHT	230
GAME_ID	22101209	FGM_PAINT	5
GAME_DATE	2022-04-08T00:00:00	FGM_2PT_MR	0
MATCHUP	DAL vs. POR	PW_MIN	109.3
WL	W	PW_GAMES	3
MIN	29.6	PW_FG3A	29
FGM	12	PW_FG2A	36
FGA	21	PW_OREB	1
FG3M	7	PW_DREB	22
FG3A	14	PW_ASTS	35
FTM	8	PW_TOV	17
FTA	11	PW_STL	4
OREB	0	PW_BLK	1
DREB	11	PW_POS	222
AST	7	PW_PF	9
TOV	5	PW_PFD	23
STL	0	PW_FGM_PAINT	14.0
BLK	1	PW_FGM_2PT_MR	5.0
PF	0	PW_PIE_AVG	0.160333
PFD	7	PW_USG_PCT_AVG	0.417
PTS	39	CAREER_INJURIES	26
USG_PCT	0.443	DAYS_LAST_INJURY	18
PIE	0.34	OUT_NEXT_GAME	0

Figure 9. Sample Game Log Data to be used in Running Hot Engine

Given the input and using a Running Hot Threshold of 50, the Running Hot Engine determines that Luka Doncic's Running Hot Index is 8.7, which is below the Running Hot Threshold of 50 [Figure 10]. Therefore the engine determines he was not 'Running Hot' (RUNNING_HOT=False) from his April 8 2022 game against the Portland Trailblazers and recommends him to play the next game on the Mavericks schedule, the last regular season game against the San Antonio Spurs on April 10. Given his OUT_NEXT_GAME value is 0, he played 28 minutes in that game, scoring 26 points.

PLAYER_NAME	Luka Doncic
GAME_DATE	2022-04-08T00:00:00
RUNNING_HOT_IDX	8.7
RUNNING_HOT	False
OUT_NEXT_GAME	0

Figure 10. Sample Running Hot Engine result for Individual Game

Analysis can be performed using previous game data to check if the Running Hot Engine would have determined if a player was "running hot" (RUNNING_HOT=True) but still played the next game on the team schedule (OUT_NEXT_GAME=0). Using all of the 2021-22 regular season game logs of Doncic on the Running Hot Engine with a threshold of 50, the analysis indicates that Doncic played five games during the regular season while "running hot" [Figure 11]. Despite the Running Hot Engine determining Doncic was "running hot" going into those five games, he did not suffer an injury in which he would miss games.

```
TOTAL GAME LOGS: 65
TOTAL RUNNING HOT IN GAME LOGS: 10
RUNNING_HOT/OUT_NEXT_GAME MATCH PERCENTAGE: 90.77%
TIMES SAT OUT NEXT GAME WHILE ABOVE RUNNING HOT THRESHOLD (50) (RECOMMENDED BY MODEL): 5
TIMES PLAYED NEXT GAME WHILE UNDER RUNNING HOT THRESHOLD (50) (RECOMMENDED BY MODEL): 54
TIMES PLAYED NEXT GAME WHILE ABOVE RUNNING HOT THRESHOLD (50) (*NOT* RECOMMENDED BY MODEL): 5
TIMES SAT NEXT GAME WHILE UNDER RUNNING HOT THRESHOLD (50) (*NOT* RECOMMENDED BY MODEL): 1
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Figure 11. Running Hot Engine Analysis (Jupyter Notebook text output)

Table 4. Games Luka Doncic played in the NBA 2021-22 Season but was determined as "running hot"

Game	Minutes	Points	Running Hot Index	Injured
4/1/2022, L @ WAS	36	36	55.8	No
3/29/2022, W vs. LAL	29	34	67.6	No
3/27/2022, W vs. UTA	36	32	55.7	No
1/19/2022, W vs. TOR	42	41	65.9	No
1/12,2022, L @ NYK	36	21	88.8	No

Though the Running Hot Engine determined Doncic was not "running hot" after the March 3, 2022 game against the Golden State Warriors, reports show he suffered a toe injury and sat out the next game on March 5 (MacMahon 2022). Given these findings, a narrative behind this analysis could show that despite their health and risk for injury, a player like Doncic is more than willing to continue playing as much as he can during the season and was able to deliver very solid performances in these potentially risky games.

Table 5. Game Luka Doncic sat out in the NBA 2021-22 season but was determined not to be 'running hot'

Game	Minutes	Points	Running Hot Index	Injured
3/3/2022, L @ GSW	40	41	29.8	Left Toe Sprain

Conclusions and recommendations

The Running Hot Engine can be used as a complementary tool to help the coaching, medical, and training staff of an NBA team make a recommendation in having a player sit out a game based on their latest game log, game activity from the past week, and injury history. While the default threshold setting is 50, the Running Hot Engine has the flexibility for an organization to set their own Running Hot Threshold as they see fit for the team holistically or specifically for individual players.

Given the engine's potential to help with decision-making, the model at its current form still has its limits. As mentioned before, there is technical debt in data collection that still needs to be resolved, and doing so would result in giving the model a much larger and richer dataset for fitting. A larger dataset can possibly help mitigate the bias and overfitting caused by the DAYS_LAST_INJURY feature. Further research into fine tuning the logistic regression model is another opportunity for improvement of the engine, as well as the possibility to research other kinds of binary classification modeling such as random forest or support vector machines (SVM). While the dataset consists of publicly accessible information provided by NBA.com and Pro Sports Transactions, integrating tracking biometric data such as speed, distance traveled during a game, heart rate, and other features and data that NBA teams are privy to, could potentially enrich the dataset even further (but at the same time being aware of HIPAA rules and regulations). At its current state, the Running Hot Engine and its model should be considered more as a proof of concept with the potential to be a complementary tool to help an organization decide when to rest players.

That being said, any NBA team should be mindful about being fully dependent on any decision engine that recommends players to rest when they are "running hot." The issue of "load management" does have an effect with fans that invest their time and money to attend games and hope to see their favorite players live. At the same time, load management is considered to help the longevity of a player's career and their health for the playoffs. It is a very delicate line to find the right balance between satisfying the fans and visitors of the game, a team’s investment into a player’s contract, and putting the team in the best position for winning a championship.

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