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Evaluating the Effect of Potential Career-Altering Injuries on NBA Athletes

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Abstract

This project aimed to evaluate the effect of three major injuries on the post-recovery performance of athletes in the National Basketball Association (NBA): anterior cruciate ligament (ACL) tears, Achilles tendon tears, and meniscus tears. All three are crucial in stabilizing the body during strenuous movements, such as pivoting, jumping, or accelerating. Recovery from these injuries takes many months and can change an athlete's career trajectory. A dataset with every NBA player who has suffered one of the three named injuries in the past twelve seasons was curated (n=113), with information about each player's overall impact on the court before and after injury and some characteristics that may determine post-injury performance. The data was run through various data analysis models, including multiple regression and decision tree classification. This study was the first to use newer statistical metrics such as LEBRON to evaluate player performances, as well as the first to combine the three injuries for direct comparison. The return rates for ACL, Achilles, and meniscus injuries were 85.7%, 96.3%, and 88.6%, respectively. Results indicated that age and average minutes per game pre-injury were the most important factors in determining a player's post-recovery performance. Furthermore, Achilles injuries harmed offensive impact more than ACL or meniscus injuries. However, they were more likely the result of over-usage and, therefore, less likely to end a player's career. Finally, those who previously suffered a similar injury performed significantly worse than those who did not.

Keywords: Anterior cruciate ligament, Achilles tendon, Meniscus, Basketball, Injury, Performance

1. Introduction

The National Basketball Association (NBA) is the professional basketball league of the United States, with players from all over the world competing in a 30-team league. The rigorous schedule of the season, which features an average of one game every three days, can take a massive toll on athletes' bodies, often in the form of injuries. Although many of these injuries permit recovery with a few days rest, some injuries, such as anterior cruciate ligament (ACL) tears, Achilles tendon tears, and meniscus tears, can be devastating and may even alter the course of a promising career. A tear in any of these areas will greatly impair an athlete's agility and speed, ravaging their ability to compete in a physical sport like basketball. The NBA has seen cases like Derrick Rose, a young star voted the league's Most Valuable Player in just his third season reduced to a bench player after multiple injuries, and others like Kevin Durant, who returned from an Achilles injury a year and a half later to play at the same all-star level.

The ACL is a ligament in the knee that runs from the back of the femur to the front of the tibia. It is a strong band of tissue that provides stability in the knee when one pivots or accelerates. Hence, ACL injuries most commonly occur during sports that require rapid changes in pace or direction, jumping, and landing, such as basketball, soccer, skiing, or football. A full tear, and often partial tears, of the ligament require surgical repair and a recovery journey of upwards of eight months (Mayo Foundation for Medical Education and Research, 2022).

The Achilles tendon is the largest tendon in the body, stretching from the bones of the heel to the calf muscles. It allows one to point their toes to the floor or raise up on their tiptoes. Achilles tendon tears are also common in activities that require rapid changes in speed or pivoting. They often occur when one suddenly starts moving, such as surging

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off the sprint block in a race. Recovery from an Achilles tear also requires surgery, while the return to sports takes anywhere between six and twelve months (Sachdev, 2021).

The meniscus is a piece of cartilage in the knee that cushions and stabilizes the joint, protecting the bones from wear and tear. Meniscus tears can happen on their own but often accompany ACL tears. The outer region of the meniscus has a good blood supply and can often heal on its own, but tears in the inner two-thirds usually require surgical repair. Still, full recovery from meniscus tears takes six to eight weeks (Wheeler, 2022).

Although injuries to the ACL and Achilles are much more devastating, the meniscus is also crucial to knee function and can cause players to miss a significant amount of playing time, usually around 8-10 weeks. The objective of this investigation is to see if there is a correlation between certain characteristics of an athlete and their performance after recovering from these three injuries using both simple calculations and machine learning models. Some hypotheses include age and previous injury having significant impacts, as older players or those who have already suffered a similar injury are less likely to recover fully. Achilles and ACL injuries are likely more severe than meniscus ones, especially for offensive play, as they require much longer rehabilitation periods and are more crucial to leg stability. The results in this study were supported with statistical methods and corroborated with previous similar studies to increase confidence in conclusions.

2. Dataset

The dataset used in this study was extracted from a larger dataset recording every injury in the NBA from the 2010 to 2020 seasons. It is available to the public on Kaggle (https://www.kaggle.com/datasets/ghopkins/nba-injuries-2010-2018). This set was filtered through to find every instance of a torn ACL, torn Achilles tendon, or a torn meniscus, and their respective players were added to a personal dataset (https://github.com/derekgao2/NBA-Injuries.git) with the following features:

- *Player* is the last name, and sometimes first initial, of the player that was injured.
- *Injury type* describes the injury with an integer: 0 for torn ACL, 1 for torn Achilles, and 2 for a torn meniscus. If a player tore both their ACL and meniscus, they were given a 0, as the ACL is the more significant injury.
- *Season* is the season that the injury occurred. For example, if a player was injured in the 2015-16 season, the year 2016 is written.
- *Age* indicates the age at which the athlete was injured
- *Height* indicates the height of the player in inches, to the nearest inch
- *Weight* indicates the weight of the player in pounds, to the nearest pound
- *Previous injury* describes the player's injury history with an integer: 0 if they have never suffered one of the three injuries at a previous moment in their careers, 1 if they have.
- *Avg minutes* indicates the average amount of minutes that player played per game in the season prior to injury.
- *LEBRON diff* is the difference in the average on the player's LEBRON score of the two seasons before injury and the two seasons post-recovery. If a player did not play two seasons before or after the injury, only one was used. Scores of -10 in this column indicate that the player did not return to play in the NBA after the injury. This usually meant that the player was never able to fully recover to compete at the NBA level again.
- *BPM diff* is the difference in the average on the player's BPM score of the two seasons before injury and the two seasons post-recovery. Again, if a player did not play two seasons before or after the injury, only one was used, and scores of -10 in this column indicate that the player did not return to play in the NBA after the injury.
- *O-LEBRON diff* is the difference in the average on the player's O-LEBRON score of the two seasons before injury and the two seasons post-recovery. If a player did not play two seasons before or after the injury, only one was used. Scores of -5 in this column indicate that the player did not return to play in the NBA after the injury.
- *D-LEBRON diff* is the difference in the average on the player's D-LEBRON score of the two seasons before injury and the two seasons post-recovery. Again, if a player did not play two seasons before or after the injury, only one was used, and scores of -5 in this column indicate that the player did not return to play in the

NBA after the injury.

- *Change* describes the impact of the injury on the player's performance with one of four integers, determined by looking at the LEBRON diff and BPM diff columns: 1 if their performance significantly decreased, 2 if their performance dropped a medium amount, 3 if there was minimal to no change, and 4 if they returned and improved.
- *O-change* describes the impact of the injury on the player's offensive performance with one of four integers, determined by looking at the O-LEBRON diff column: 1 if their performance significantly decreased, 2 if their performance dropped a medium amount, 3 if there was minimal to no change, and 4 if they returned and improved
- *D-change* describes the impact of the injury on the player's defensive performance with one of four integers, determined by looking at the D-LEBRON diff column: 1 if their performance significantly decreased, 2 if their performance dropped a medium amount, 3 if there was minimal to no change, and 4 if they returned and improved.

In total, data was collected on 113 players, with 42 ACL injuries, 27 Achilles injuries, and 44 meniscus injuries. A total of twelve players never returned to the NBA, with six, one, and five suffering ACL, Achilles, and meniscus injuries, respectively.

One thing to note is that current defensive metrics for the NBA are generally poor, as defensive impact is much harder to measure than offensive. Most analytics teams do not trust them, and thus the values and results stemming from this column are less significant and much more subject to chance or human error. All continuous data was scaled and normalized before being run through the regression models.

3. Methods

Two statistical metrics were used in evaluating player performances. The first was a Luck-adjusted player Estimate using a Box prior Regularized On-off (LEBRON), which evaluates a player's total impact per 100 possessions. Each player's estimated impact is stabilized by adjusting for their offensive role. For example, three-point shots will not be weighted the same for sharpshooters who specialize in these shots, versus centers who set screens for their teammates to create open shots (Medvedovsky, 2022). It is then adjusted for luck, as team performances are not completely dependent on a single player. For example, a star athlete cannot control their opponent’s three-point percentage or whether or not a teammate misses a free throw. Both of these can help or hurt their overall measured impacts when they are on the floor (Goldstein, 2018). LEBRON is one of the most accurate statistical metrics currently available due to the wide variety of factors it considers for each player. Its holistic evaluation of each athlete was very relevant to the research question because of its ability to precisely capture athletes’ post-recovery performances within a single number.

LEBRON is also split into two categories: O-LEBRON, which measures offensive impact per 100 possessions, and D-LEBRON, which measures defensive impact per 100 possessions. The LEBRON score of a player is the sum of their O-LEBRON and D-LEBRON scores. Each player is given a single value in these three metrics for each season. (Narsu & McBasketball, 2022). The dataset can be found at https://www.bball-index.com/lebron-database/.

The other metric used was Box Plus-Minus (BPM), which measures a player's quality and contribution to the team from play-by-play regression with a value from -10 to 10. It uses a player’s box score information, position, and the team’s overall performance to estimate the player’s contribution in points above the league average per 100 possessions played. It starts by assuming that every player on the team has contributed equally, then factors in all of the box score data relative to the other players on the team. Players are given a single value for each season (Myers, 2020). The dataset can be found at https://www.basketball-reference.com/leagues/NBA_2023_advanced.html. Although BPM may not be as accurate as LEBRON, it is still considered a strong statistical metric in evaluating athlete performances and is useful to this research because it provides a second value to corroborate with the LEBRON values. Furthermore, it compares a player to the league average, so it is easier to see the impact of an injury to a player’s post-recovery performance.

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The regression models used were multiple regression (MR) and decision tree classification (DTC). These methods were used to find a correlation between the player characteristics and their post-recovery performances, indicated in the change, o-change, and d-change columns. The two-sample t-test was also used to corroborate the results. Finally, simpler calculations included averaging the values in the LEBRON diff, BPM diff, O-LEBRON diff, and D-LEBRON diff columns and comparing them based on the type of injury and injury history.

3.1 Multiple Regression

One limitation of linear regression, a common method used in searching for correlations in data, is that it can only look at one independent variable at a time to predict the dependent variable. In this case, many independent variables may work together to determine the dependent variable, so multiple regression was used. Consider the formula of MR:

$$y = a_1 n_1 + a_2 n_2 + a_3 n_3 + \cdots + a_i n_i + b$$

Where y is the calculated dependent variable, $n_1, n_2, .\ n_i$ are the i independent variables, and $a_1, a_2, . . a_i$ are the calculated coefficients for the different independent variables. Given specific values for each of the independent variables, plugging them into the equation should give the most likely change in performance. A percentage of the dataset was used to train the model, and the rest was used to test it. The R^2 score measures the model's validity using the testing data points.

3.2 Decision Tree Classification

The decision tree model is based on a tree-like structure and aims to predict the class of a target variable, in this case, the value in the change, o-change, or d-change columns. The root node, or the uppermost node, represents the entire sample of data. As the model progresses, nodes are split into two or more sub-nodes as the data is categorized and decisions are made. Nodes that do not split are called leaf or terminal nodes, representing the classes of the target variable. Decision trees are advantageous because they provide a non-linear model, much like multiple regression. However, it forces consideration of all possible outcomes of a decision and traces each path to a conclusion, allowing for much more thorough evaluation. A visualization of a decision tree in XGBoost, a gradient-boosted decision tree machine learning library, is shown in Figure 1.

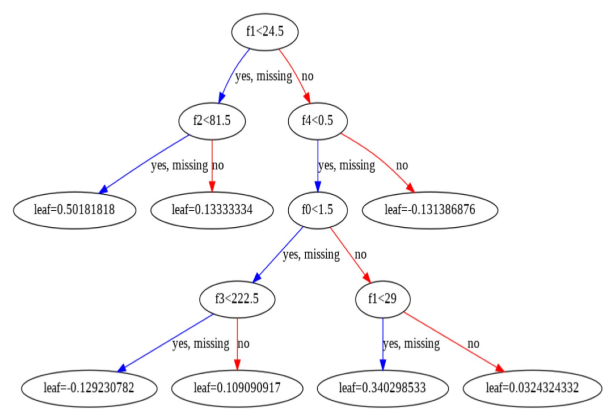

Figure 1. XGBoost decision Tree Structure

3.3 Student's T-Test

The two-sample t-test is a method used to test how significant the difference between two population means is. This is useful when attempting to determine whether the difference between two groups of data is statistically significant or simply due to random chance. It always starts with the null hypothesis that the two population means are equal and looks to reject it. The equation for the *t*-value is:

$$\frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

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Where $\overline{x_1}$ and $\overline{x_2}$ are the corresponding means of the populations, n_1 and n_2 are their population sizes, and s_1 and s_2 are their standard deviations. Note that this calculation is only used when the variances of the two populations are not equal. If the variances are equal, t would be calculated as:

$$\frac{\overline{x_1}-\overline{x_2}}{s_p\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \quad \text{where } s_p = \frac{\left((n_1-1)s_1^2\right)+\left((n_2-1)s_2^2\right)}{n_1+n_2-2}$$

Along with the student's t-test, a corresponding *p*-value is calculated. This value represents the probability that one can reject the null hypothesis. The smaller the *p*-value, the greater the probability that the difference between the two datasets is statistically significant. A *p*-value below 0.05 indicates that one can be 95% confident that the difference seen in the two groups is due to correlation and not due random chance, and is often the threshold to determining statistical significance. Thus, the calculated *p*-values that fit this criterion were recorded in a table.

4. Results

The return rates for ACL, Achilles, and meniscus injuries were 85.7%, 96.3%, and 88.6%, respectively. The average ages of a player at the time of injury were 25 years 10 months, 28 years 7 months, and 26 years 9 months for ACL, Achilles, and meniscus injuries, respectively. On average, a player's LEBRON score decreased by 0.412, 0.969, and 0.458 for ACL, Achilles, and meniscus injuries, respectively, and a player's BPM score decreased by 0.865, 1.573, and 0.477, respectively (Figure 2). Figure 3 shows the average decrease in O-LEBRON and D-LEBRON scores for each injury. Players were also split based on whether or not they had been previously injured, and the average decrease in all four metrics was calculated (Figure 4).

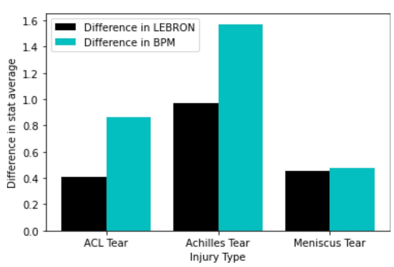

Figure 2. Average Decrease in Performance by Injury

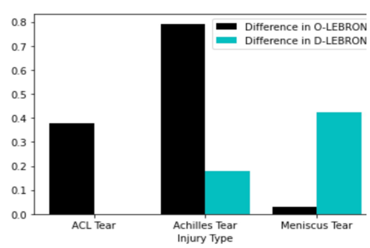

Figure 3. Average Decrease in Offensive and Defensive Performance by Injury

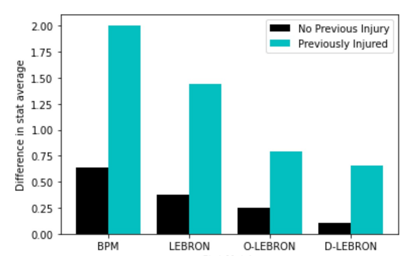

Figure 4. Average Decrease in Performance based on Injury History

Note that for all of the above results, if a player did not return to the NBA after the injury, they were not included in the calculations.

Next, each independent variable was graphed with each metric. The only graphs in which a general downward trend was noticeable were the ones that graphed athlete's ages. The older an athlete at the time of injury, the worse their performance post-recovery (Figure 5). Still, there were players of all ages that never returned to play, as indicated by the range of data points at the bottom of the graph. Furthermore, this trend was only noticed in three of the metrics. Age did not seem to have an impact on an athlete's defensive ability post-injury. (Figure 6). Finally, the majority of players evaluated averaged over 25 minutes per game. However, all 12 players who never returned to play averaged below 25 minutes per game in the season prior to injury (Figure 7).

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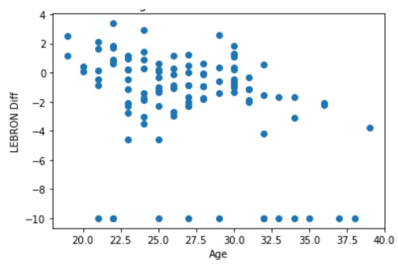

Figure 5. Age vs. Difference in LEBRON

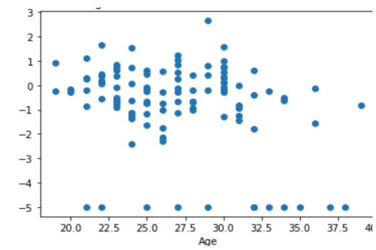

Figure 6. Age vs. Difference in D-LEBRON

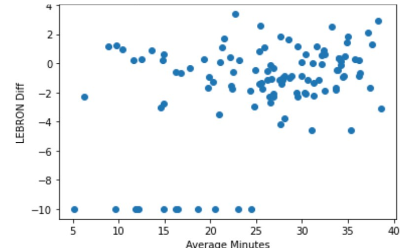

Figure 7. Average Minutes vs. Difference in LEBRON

4.1 Student's T-Test

Any player who did not return to play in the NBA was again removed before performing any calculations in this section. A knee injury combines results from ACL and meniscus injuries. Table 1 shows the most significant *p*-values resulting from two-sample t-tests. For example, in row 5, players who had suffered previous injuries performed much worse after recovering when compared to those who had not been previously injured (-1.44 compared to -0.37). The low corresponding *p*-value indicates that one can be confident this difference is in fact due to their injury history and not random chance.

Table 1. Arrays of Data Compared and Corresponding *p*-Values

Independent Variable 1	**Independent Variable 2**	**Dependent Variable**	**Independent Variable 1 Avg ± SD**	**Independent Variable 2 Avg ± SD**	***p*-value**
ACL Injury	Achilles Injury	Age	25.857 ± 4.45	28.593 ± 3.22	0.00026
Meniscus Injury	Achilles Injury	Age	26.773 ± 4.58	28.593 ± 3.22	0.02226
Meniscus Injury	Achilles Injury	Offensive LEBRON Difference	-0.029 ± 1.26	-0.792 ± 0.98	0.01127
Knee Injury	Achilles Injury	Offensive LEBRON Difference	-0.197 ± 1.30	-0.792 ± 0.98	0.03554
Previous Injury	No Previous Injury	LEBRON Difference	-1.444 ± 1.57	-0.371 ± 1.56	0.00831
Previous Injury	No Previous Injury	BPM Difference	-2.005 ± 2.60	-0.641 ± 2.57	0.04160
Previous Injury	No Previous Injury	Defensive LEBRON Difference	-0.661 ± 0.90	-0.106 ± 0.86	0.01400

4.2 Multiple Regression

Figure 8 shows the predicted values of BPM differences for the data used to test the model graphed with their actual values. The R^2 score for this model was 0.349.

4.3 Decision Tree Classification

A decision tree model was run three separate times to predict the values in the change, o-change, and d-change columns, receiving accuracy scores of 0.462, 0.447, and 0.308, respectively. The graphs indicating the relative importance of each independent factor for each model are shown in figures 9, 10, and 11.

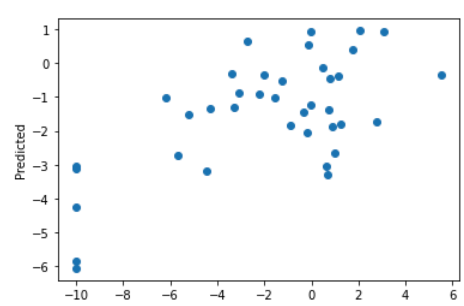

Figure 8. Multiple Regression Model for BPM Differences: Predicted vs. Actual Values

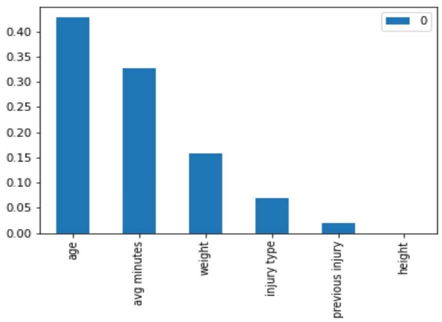

Figure 9. Relative importance of each independent factor in determining overall impact post-recovery

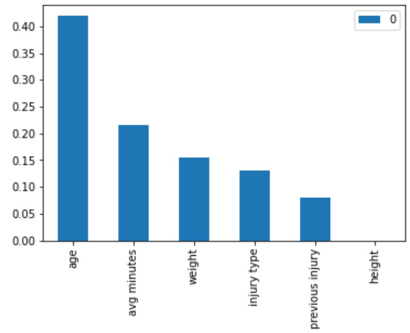

Figure 10. Relative importance of each independent factor in determining offensive impact post-recovery

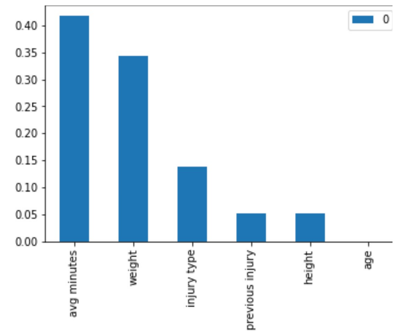

Figure 11. Relative importance of each independent factor in determining defensive impact post-recovery

Here is the confusion matrix for the overall change decision tree model:

$$\begin{bmatrix} 5 & 0 & 0 & 2 \\ 1 & 9 & 1 & 3 \\ 1 & 8 & 0 & 0 \\ 0 & 4 & 1 & 4 \end{bmatrix}$$

The sum of the numbers in the *i*th row is the total number of data points classified by *i*, while the number in the *j*th column of the *i*th row is the number of data points the model predicted to be *j* but was actually *i*. For example, there were 14 players classified by 2, meaning their performance dropped a medium amount, and the model predicted 9 of these players correctly. Here is the confusion matrix for the offensive change decision tree model:

$$\begin{bmatrix} 4 & 4 & 0 & 4 \\ 1 & 9 & 0 & 3 \\ 1 & 2 & 0 & 1 \\ 1 & 4 & 0 & 4 \end{bmatrix}$$

5. Discussion

5.1 Interpretations

Some of the results from this study are supported by common intuition. For example, age was a significant factor in determining a player's post-recovery performance. The older the player, the less of an impact they had on the floor, which makes sense because as a player ages, they can no longer play with the same intensity and aggressiveness as they could have if they were five or ten years younger (Figure 5). An injury only accelerates this decline. Furthermore, players who had previously suffered a similar injury performed significantly worse in almost every metric than those who did not (Table 1 & Figure 4), as second major surgery can take a serious toll on an athlete's body, especially if they are a couple of years older at the time of the repeat injury.

All three injuries caused decreases in overall, offensive, and defensive impact (Figures 2 & 3). Furthermore, an Achilles tear caused the worst decrease in offensive LEBRON, as indicated by Table 1, while the differences among the injuries in overall and defensive performances were statistically insignificant. This result corroborates with the findings of Benjamin Kester (2016) and Lafi Khalil (2020) who both concluded that ACL and Achilles injuries significantly harm player performances post-recovery. Taken together, these three studies support the conclusion that the Achilles and ACL tissues are very crucial to a player's impact on the court, as speed, agility, and explosiveness are all crucial to the sport. On the other hand, the data was swapped for the meniscus (Figure 3), with more damage being done to a player's defensive impact but little change to offensive impact. One possible explanation is that more jumping occurs during defense as players go up to contest shots or layups, and the meniscus acts as a shock absorber during

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hard landings.

One interesting result was that all twelve players who did not return to play averaged 25 minutes per game or less, while the majority of the other players averaged more (Figure 7). This result could be because players who average more time on the court are the ones who are capable of playing at a higher level and thus can take a setback to their careers, while bench players who already have limited roles will be cut without a second thought. Furthermore, six of these players suffered an ACL injury, five suffered a meniscus injury, but only one suffered a torn Achilles. These numbers suggest that although a torn Achilles has a larger impact on post-recovery performance, it is unlikely to end a career. Using the above logic, it is possible that an Achilles injury only occurs when a player reaches a decently high level of play and averages a significant number of minutes per night, meaning that the injury might result from wear and tear rather than a single freak accident. This conclusion is further supported by the extremely low p-values in the t-test results, which showed that the difference between the average ages of players who suffered each of the three injuries is statistically significant. Those who suffered Achilles injuries were on average three years older than those who suffered ACL injuries and two years older than those who suffered meniscus injuries, meaning that an Achilles tear usually occurs later into an athlete's career and thus is more likely the result of overuse. On the other hand, ACL and meniscus injuries occur earlier, which could be because these types of injuries occur much more suddenly.

The R^2 score for the multiple regression model of prediction was relatively low (Figure 8), indicating a poor and unreliable model for this dataset. The decision tree models scored a little bit better, however. It was trained to place each player into four classes, so a randomly guessing model would have had an accuracy score of around 25%. The models predicting change and offensive change were closer to 45%, meaning that although not ideal, they were much better than a random guess. Furthermore, many of the predictions were close, as seen in the decision matrix for the decision tree that predicted overall change. Since classes 2 and 3 were the most similar, with the former being medium change and the latter being little change, it makes sense that the model may have mixed them up. In both the overall and offensive change models, the order of the relative importance of each independent factor was the same. Age and average minutes were the two most important, which aligns with the results above (Figures 9, 10, & 11).

5.2 Limitations

The major limitation of this study was the paucity of data. ACL, Achilles, and meniscus injuries are not the most common types of injuries in the NBA, leaving the dataset used in this study to only include 113 players. With a smaller dataset, the models did not have as much information to create the ideal predictions, thus leading to the lower accuracy scores. Furthermore, LEBRON scores have only been calculated for players since 2010, meaning that any injuries prior to the 2009-10 season could not have been used in this study.

It is also possible that players' performances correlate more with their rehabilitation process rather than their physical traits like height or weight. Numbers such as hours spent in physical therapy or time between different stages of recovery may have been able to produce more accurate predictions in the decision tree models. Unfortunately, data on an individual athlete's path to recovery is not available for public use. Hopefully, future studies will be able to incorporate such data.

5.3 Next Steps

As stated above, there is data on NBA injuries that goes farther back than the 2009-10 season, but a different statistic than LEBRON would have to be used. Most of the current advanced statistics that evaluate a player's overall impact on the court are relatively new and likely don't go much further into the past either. Still, this study could be applied to more simple statistics like field goal percentage or points/rebounds/assists per game.

Other paths could include extending this analysis to the National Collegiate Athletic Association (NCAA), the college sports league that hosts the famous March Madness tournament every year. The same investigation could even be extended to other significant injuries in other sports, such as ulnar collateral ligament (UCL) injuries in the elbow joint for baseball pitchers.

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6 Conclusion

This study offered insight into the relative severities of ACL, Achilles, and meniscus tears and how they may impact an NBA athlete's post-recovery performance in spite of high return rates. Older age and injury history played definite roles in decreasing the LEBRON and BPM scores of an athlete, while averaging greater minutes per game may prevent one's career from coming to a brutal end. One crucial hypothesis derived from this study is that Achilles injuries are more harmful but more likely to be the consequence of over-usage than ACL ones, which can result from a single misplaced pivot foot. Additional research should be completed in the future as data accumulates, allowing for more generalized results and, therefore, a greater chance to predict and prevent these injuries.

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