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Sports Analytics and Text Mining NBA Data to Assess Recovery from Injuries and Their Economic Impact

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Abstract: Injuries are an unfortunate part of professional sports. This study aims to explore the multi-dimensional impact of injuries in professional basketball, focusing on player performance, team dynamics, and economic outcomes. Employing advanced machine learning and text mining techniques on suitably preprocessed NBA data, we examined the intricate interplay between injury and performance metrics. Our findings reveal that specific anatomical sub-areas, notably knees, ankles, and thighs, are crucial for athletic performance and injury prevention. The analysis revealed the significant economic burden that certain injuries impose on teams, necessitating comprehensive long-term strategies for injury management. The results provide valuable insights into the distribution of injuries and their varied effects, which are essential for developing effective prevention and economic strategies in basketball. By illuminating how injuries influence performance and recovery dynamics, this research offers comprehensive insights that are beneficial for NBA teams, healthcare professionals, medical staff, and trainers, paving the way for enhanced player care and optimized performance strategies.

Keywords: basketball analytics; data analysis; data science; injury analytics; sports analytics; text mining

Citation: Sarlis, V.; Papageorgiou, G.; Tjortjis, C. Sports Analytics and Text Mining NBA Data to Assess Recovery from Injuries and Their Economic Impact. *Computers* **2023**, *12*, 261. https://doi.org/10.3390/computers12120261

Academic Editor: Paolo Bellavista

Received: 23 November 2023
Revised: 10 December 2023
Accepted: 12 December 2023
Published: 16 December 2023

1. Introduction

Sports analytics have found a strong position in the realm of sports, particularly in predicting potential setbacks and optimizing team and player performance. This is evident in diverse applications, from aiding team management in estimating and mitigating injury risks to assisting betting companies in forecasting player and team performance. The overarching goal remains consistent: to reduce associated costs and elevate performance metrics, either for an individual player or the entire team [1–4]. Engaging in sports boasts numerous advantages but also leads to injuries. Several parameters, such as age, sex, sport nature (contact or noncontact), and training intensity, govern the susceptibility of athletes to injuries [5,6].

According to the National Basket Association (NBA), injuries are a significant concern, as they can potentially detrimentally impact player performance. Although advancements have been made in prevention and rehabilitation, injury rates remain alarmingly high. This unpredictability in injury occurrence can be attributed to various factors, many of which are challenging to pinpoint and measure. Furthermore, the repercussions of such injuries are not only felt by players but also by management, fans, teams, and their overall dynamics [7,8].

Basketball's universal appeal, much of which can be credited to the NBA's prominence, spans from casual games to professional tournaments. The influence of the NBA is undeniable, impacting not only the sport's popularity but also the socioeconomic narratives of players, teams, and the league itself [9,10].

The proliferation of big data has revolutionized how sports professionals, from trainers to healthcare experts, approach injury management. With the advent of biometric tracking tools such as accelerometers, RFID devices, HR monitors, and GPS wearables, the ability to diagnose team or player vulnerabilities has improved. These technologies play pivotal roles in refining performance, curtailing injury risks, and accelerating recovery trajectories [11–13].

An injury can have a significant impact on the economic data of a team. A key player sustaining an injury can cause a decline in team performance and ultimately affect revenues and profitability, as it can lead to a decrease in ticket and merchandise sales. If a player is not able to fully recover from an injury, this can cause a decline in their performance on the court and ultimately affect the team's overall performance [14–17].

Another study reviewed in-depth injury analysis from the 2017–2021 NBA seasons. There was a rise in injuries and games missed, with the highest injury rates for guards and athletes with 6–15 years of experience. This study underscores the necessity of further research to understand and reduce injury risks in professional basketball [18].

This can also lead to a decline in revenue from sponsorships and advertising. Additionally, injuries can affect a team's salary cap, which is the amount of money that the team has available to spend on player salaries. If a player sustains an injury, they may not be able to perform at the same level as they did before, which can affect their future salary and contract negotiations. This can also affect the team's ability to sign new players, as they may have less money available to spend on player salaries. Overall, an injury can have a significant impact on the economic data of a team. Although the immediate effect may be a decrease in attendance, merchandise sales and revenue from sponsorship, the long-term effect can be a negative impact on a team's overall performance, attendance, merchandise sales, revenue from sponsorship, salary cap, and ability to sign new players [19–21].

Researchers have investigated the use of a new ML approach to detect injury risk factors in young team-sport athletes [9]. The results showed that the new approach was effective at detecting injury risk factors and could be a useful tool in injury prevention and risk management.

Several researchers have investigated the knee movement patterns of injured and uninjured adolescent basketball players when landing from a jump. The authors conducted a case–control study and reported that injured players had different knee movement patterns than uninjured players when landing. The results suggest that certain knee movement patterns may contribute to an increased risk of injury in adolescent basketball players [22,23].

In one study, researchers identified the use of ML in classifying the integrity of articular cartilage in the knee joint. They used near-infrared spectroscopy to gather data on the biochemical composition of cartilage samples. Afterward, they applied ML algorithms to the data to classify the cartilage samples into categories of different levels of integrity. The results showed that the ML approach was able to accurately classify the samples, suggesting that the ML approach could be a useful tool for detecting and monitoring cartilage degradation in the knee joint [24–26].

The subsequent sections methodically explore the intricate connections between injuries and player performance, the economic repercussions for teams, and the efficacy of modern data science methodologies in addressing these challenges. Section 2, 'Data and Methods' details our approach, employing advanced data analytics and text mining techniques to scrutinize injury patterns and their impacts. Section 3, 'Results,' presents our findings, highlighting the significant influence of injuries on both player performance and team economics. Finally, in Section 4, 'Discussion',' we interpret these findings, offering insights into the broader implications for injury prevention, team management strategies, and future research directions in the domain of sports analytics. This research aims to explore the multi-dimensional impact of injuries in professional basketball, with a focus on player performance, team dynamics, and economic outcomes. Utilizing text mining techniques on NBA data, this study examines the complex relationship between injury and performance metrics, revealing the significance of certain anatomical sub-areas. The analysis also uncovers the substantial economic burden that injuries impose on teams, highlighting the need for comprehensive, long-term strategies for injury management. The broader objectives of this research are to provide valuable insights into the distribution of injuries and their varied effects, which are crucial for developing effective prevention strategies and economic approaches in basketball. By illuminating the influence of injuries on performance and recovery dynamics, this study offers comprehensive insights beneficial to NBA teams, healthcare professionals, medical staff, and trainers. This contributes to enhancing player care and optimizing performance strategies. This study methodically explores the connections between injuries and player performance, the economic repercussions for teams, and the efficacy of modern data science methodologies in addressing these challenges By synthesizing data-driven analysis with practical considerations, this paper aims to contribute a comprehensive perspective on the complexities and nuances of managing sports injuries in the high-stakes environment of professional basketball.

2. Data and Methods

We aimed to apply advanced data analytics and text mining techniques to study the influence of sports injuries on athlete performance, recovery dynamics, and economic implications for basketball teams. These objectives were achieved using text mining to find patterns among specific anatomical injury sub-areas and shifts in advanced performance indicators across series (2-game, 5-game, and 10-game) were delineated. Subsequent analyses examined the recovery trajectories of patients with different injury types, elucidating the factors influencing recovery duration. Economic ramifications were assessed by scrutinizing the perturbations in pertinent basketball analytics post-injury events.

2.1. Research Questions/Hypothesis

1. Is it possible, using text mining, to distinguish patterns and relationships between references to injuries of anatomical sub-areas and changes in advanced performance indicators across different series, such as 2-game, 5-game, and 10-game series? (RQ1)
2. Which types of injuries take longer for athletes to recover from before they can return to action? (RQ2)
3. How do the different injury types vary in correlation with advanced basketball performance metrics? (RQ3)
4. How does an injury affect the economic data of a team based on basketball analytics? (RQ4)

2.2. Methodology

This study utilized data from multiple sources [27–29] to ensure comprehensive information for a robust analysis. Extensive data scraping and preprocessing techniques were utilized. Data was collected for NBA players' performance, injuries, and salaries from the 2000-01 to 2022-23 seasons using the nba_api to extract data from the NBA's official website [29] and then consolidated into one dataset based on the data cross-validation, without the information fulfillment and features-addition of the other data source [27,28]. Data retrieval and preprocessing were challenging and involved consolidating data into a supervised model and prioritizing the quality of the data. Our methodology encompasses two dimensions, Data Collection and Data Analysis, as detailed in the following subsections, and it includes data collection, preprocessing, analysis, and results evaluation [30]. Figure 1 presents the methodology outlined for this manuscript. Each step in the process is clearly delineated, providing a concise overview of the sequence from the data collection to the final analysis phases, including injury- and salary-data transformation. The preprocessing included removing irrelevant data, employing text mining to extract detailed information from textual descriptions of injuries and player contracts, and standardizing salary figures with inflation rates. The final dataset, containing 749,631 records across 158 columns, was meticulously prepared for analysis by sorting and dividing into subsets focused on performance and injury data, ensuring a thorough and detailed approach to data analysis.

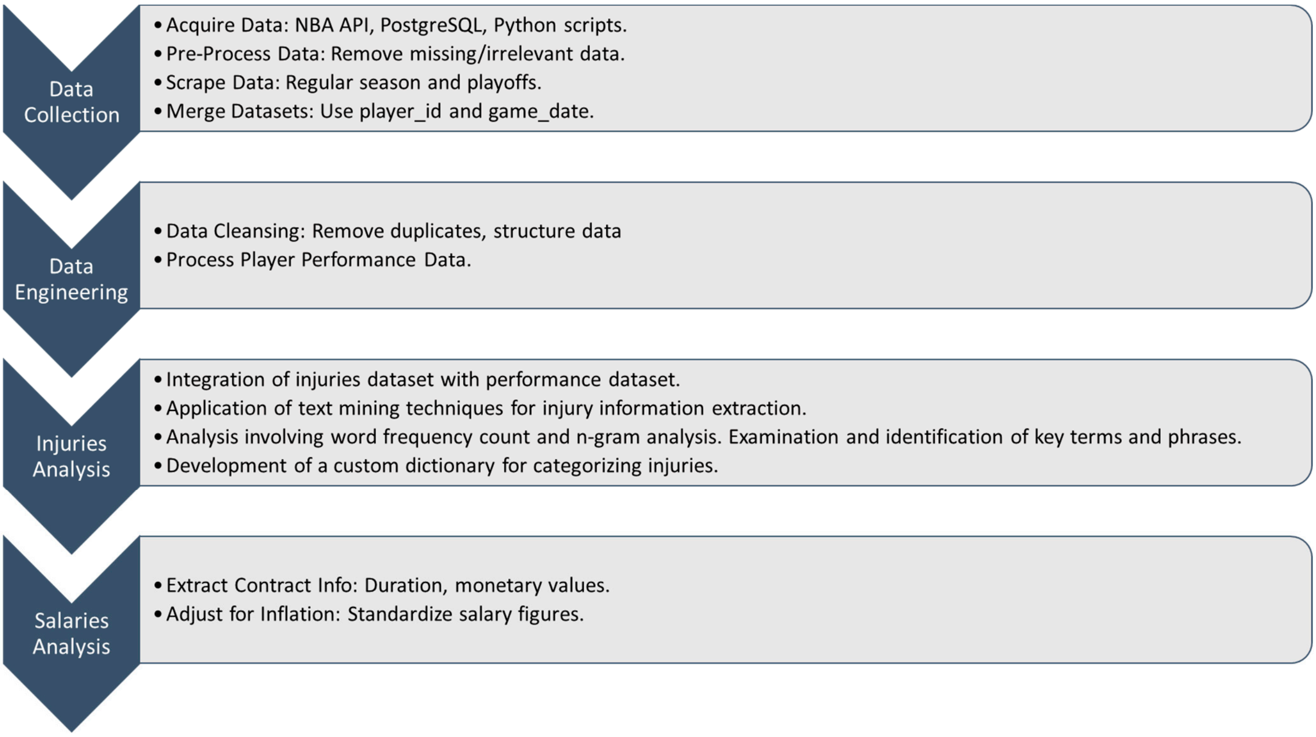

Figure 1. Structure and flow of the methodological approach.

2.2.1. Data Collection

The data collection involved handling disorganized and diverse data. The methodology included gathering, text mining, preprocessing, analysis, and result evaluation. We used Python scripts and KNIME Analytics Platform flows for data acquisition. Preprocessing included identifying and removing missing and irrelevant data. The data underwent Extract, Transform, and Load (ETL) processing using the NBA API, PostgreSQL, and Python scripts.

Our study acquired and analyzed a comprehensive dataset covering player performance, injuries, and salaries for NBA players from the 2000-01 and 2022-23 seasons. This section details the data sources, types, and dataset shapes. Player performance and injury data were obtained from the nba_api through the extraction of data from the NBA's official website and database. Web scraping occurred from 2000-01 to 2022-23, involving 2296 players across those seasons. [29].

We conducted two scrape runs: one for regular season per-game_date player performance and another for playoffs. We compiled nine distinct datasets (leaguegamelog, players, boxscoreadvanced, boxscorefourfactors, boxscoremisc, boxscoreplayertrack, boxscorescoring, boxscoretraditional, and boxscoreusage). These datasets were merged using player_id and game_date, creating a complete dataset stored in the PostgreSQL database.

Additionally, the datasets included comment-based metadata explaining player absences, including coaching decisions and injuries. A schema summary of the datasets used is given in Table 1.

Table 1. Datasets based on player performance metrics (regular and playoff season) and injury and salaries analytics for the period from 2000 to 2023.

Name	Type	# Records	# Features
Player performance statistics	Regular	733193	132
Player performance statistics	Playoffs	48213	132
Injury data	On and off game	58151	4
Salaries data	Per season	15365	4

2.2.2. Data Engineering

After the raw data were acquired, the next phase involved data engineering. This section explains the processes for data cleansing, structuring, and enhancing the collected data to prepare them for detailed analysis.

Preprocessing Player Performance Data

The player performance dataset included a comprehensive array of advanced player statistics on a per-game–date basis, including various key performance indicators (KPIs). These KPIs covered general player information, advanced box score stats, "Four Factors", miscellaneous metrics, player tracking, traditional scoring, and usage stats. "Four Factors" is a strategic framework focusing on key elements that significantly influence game outcomes. These factors include efficient shooting, characterized by high field goal percentages; ball control, emphasizing minimal turnovers; rebounding prowess, both offensive and defensive; and frequent, effective trips to the free-throw line. Dean's methodology highlights the importance of these aspects in determining a team's success on the court, offering a comprehensive blueprint for aspiring players and coaches to enhance their performance and strategies [31,32].

Although not all KPIs were consistently available throughout the entire data scraping period (e.g., specific advanced performance statistics were absent in earlier years, as in 2000), we decided to retain as much relevant information as possible for our comprehensive analysis. Duplicate records, particularly those related to primary player reference information such as player_name, were identified and removed.

Injuries Text Mining and Categorization (RQ1)

The injury dataset obtained via nba_api was integrated with our performance dataset. This integration involved adding a comment column within each performance sub-dataset, containing textual descriptions of player injuries. Due to the absence of standardized formats in these comments, we applied text mining techniques to extract injury information.

Next, a comprehensive analysis of injury text records and an initial exploratory analysis were conducted involving word frequency counts to identify the prominent terms (258 unique terms) within injury descriptions. First, we ensured that common stop words, such as "and", "in", and "on", as well as positional words such as "left" and "right", were filtered out to highlight the pertinent terms.

Subsequently, an n-gram analysis was performed, accounting for injuries, whose descriptions might contain "n" consecutive words for clarity, e.g., "strain knee". From both our single-word and n-gram" analyses (e.g., 4451 bigram terms), we correctly identified the key aspects of all injuries.

Furthermore, a qualitative examination was crucial. By manually inspecting our results, we identified key terms and phrases that accurately represented the nature and body areas of the injuries. Using these keywords, we formulated our categorization system, wherein each injury description was mapped to a specific category or injury area. As a result, we developed a customized dictionary to classify injuries into predefined categories (244 unique terms).

In the final stage of our mapping, we utilized a predefined map for injuries based on body regions [11], culminating in detailed anatomical sub-areas. For instance, a comment such as “placed on IL with sprained left ankle/right ankle” was categorized as “sprained ankle” for the injury, and “ankle” as the anatomical sub-area.

Moreover, the dataset included multiple duplicates arising from cases where a player missed more than one game due to injury. To address this, we identified and retained only the initial instance and the date of the initial injury occurrence based on specific conditions. Consequently, after mapping the textual descriptions, records were flagged as ‘duplicate = TRUE’ if they referred to the same type of injury for the same player within a 15-day window from the last reported occurrence of that specific injury type.

Salaries-Data Transformation (RQ2)

To convert the contracts dataset into a more analytically valuable salaries dataset, we employed text mining techniques once again. This involved extracting contract durations and monetary values from the textual descriptions within the scraped data. For example, a contract described as a “signed restricted free agent (from Clippers) to a 6-year, USD 51 M contract” was parsed to determine its length (6 years) and amount (USD 51 million).

Additionally, we incorporated the inflation rate in the data from [33,34] to standardize the salary figures. This adjustment allowed for more meaningful comparisons of player salaries, considering the year the contract was signed and the economic context in the U.S., where the NBA operates.

2.2.3. Data Analysis

The final dataset for this study resulted from complex data integration, incorporating advanced performance metrics, injury records, and salary data from the 2000-01 to 2022-23 regular and playoff seasons. This comprehensive dataset comprises 749,631 records across 158 columns, encompassing player performance, injury history, and financials.

Primary Data Structure

Before the analytical procedures, this merged dataset underwent two additional preprocessing steps. First, records were sorted by player_name and game_date to ensure a sequential arrangement for each player. The dataset was subsequently divided into two datasets:

1. **Performance**: Data with non-null game dates and performance metrics.
2. **Injury**: Data with non-null injury dates.

Statistical Evaluations

Two statistical tests were applied to the performance data:

1. **Paired Sample *t*-test:** Compared pre- and post-injury performance means were compared, providing t-statistics and *p*-values for each performance metric.
2. **Effect Size Estimation:** Cohen’s D was used to measure differences between pre- and post-injury performance metrics.

Summary of Statistics

In summary, we compiled comprehensive summary statistics:

1. **Unique Players:** Determined the number of total unique players and those meeting the analysis criteria.
2. **Non-NA Records:** Counted non-null data points for pre- and post-injury performance metrics.
3. **Injury Incidence and** criteria metrics: Total injuries were calculated for those meeting specific criteria.

The results were stored in a PostgreSQL database and organized for subsequent exploratory data analysis and hypothesis testing.

3. Results

In this section, the results show the effects of injuries on basketball players' performance by comparing a series of performance metrics captured during two, five, and ten games before and after injury events. Combining Cohen's D with the t-test in research provides a more comprehensive understanding of the data's statistical significance and practical importance in evaluating effect sizes in analysis. The Cohen's D thresholds 0.2–0.5 for Small, 0.5–0.8 for Medium, and greater than 0.8 for Large Effect are used in science and represent standard benchmarks for interpreting the magnitude of an effect size, regardless of the direction (positive or negative) of the effect. In the context of our research, t-tests were used to identify metrics that showed significant differences pre- and post-injury. Hence, Cohen's D was used to categorize these differences into small, medium, or large effects. This combination of tests allows us not only to report which differences are statistically significant but also to refer to the practical implications of these differences based on their magnitude. Utilizing statistical methods to assess the significance and magnitude of changes in player efficiency, we aimed to reveal actionable insights into the impact of injuries [35–37]. This study not only quantifies the immediate and short-term implications of injuries but also contributes to the strategic planning of player recovery and game strategy, offering a valuable resource for coaches, medical staff, and sports analysts.

Tables 2–4 show the results of analyzing anatomical sub-areas in correlation with the significance of the dataset's performance metrics, as stated in A1 table of the Appendix, the effect size, and the average percentage of change in 2-, 5- and 10-game series **(RQ1)**.

Two Games before/after the injury.

Areas with Significant Impact:

- The anatomical sub-areas that had statistically significant impacts (p-values less than 0.05) included the ankle, knee, thigh, and abdominal areas and many others, totaling 18 different areas.
- **Cohen's–D and t-statistic:**
    - **Large Effect** (>0.8): No areas with a large effect size were identified.
    - **Medium Effect** (0.5–0.8): No areas with a medium effect size were identified.
    - **Small Effect** (0.2–0.5): The upper arm and forearm area was the only area with a small effect size.

Percentage Change:

- **Most Impacted**: The abdominal area experienced the most significant average percentage change, suggesting a considerable decrease in performance metrics post-injury.
- **Least Impacted**: The chest area was the least impacted based on the average percentage change, indicating a less substantial decrease in performance.

Areas of Concern:

- The areas of concern due to significant p-values, but smaller effect sizes included the ankle, knee, and thigh areas and several others, highlighting the need for careful consideration of both statistical significance and effect size.

Table 2. Two Games before/after the injury.

Anatomical sub-areas	Avg. p-value	Median p-value	Avg. t-statistic	Median t-statistic	Avg. Cohen's D	Median Cohen's D	Average of Avg. Percentage Change	Median Avg. Percentage Change
Ankle	1.03×10^{-28}	1.11×10^{-68}	18.77	19.18	−0.40	−0.41	−18.73	−21.97
Knee	2.78×10^{-39}	1.33×10^{-45}	16.29	14.39	−0.32	−0.28	−14.00	−15.47
Thigh	7.85×10^{-20}	4.45×10^{-31}	12.45	12.41	−0.38	−0.40	−15.60	−17.80
Abdominal	8.68×10^{-06}	1.82×10^{-28}	10.80	11.68	−0.54	−0.58	−28.09	−29.06
Foot	3.67×10^{-17}	4.80×10^{-25}	11.12	10.62	−0.41	−0.39	−23.16	−24.21
Thoracolumbar	5.98×10^{-14}	9.26×10^{-21}	10.53	9.48	−0.30	−0.28	−11.32	−10.69
Hand–Thumb–Fingers	5.73×10^{-06}	2.67×10^{-18}	8.55	9.03	−0.38	−0.40	−14.90	−16.58

Hip	8.72×10^{-11}	2.19×10^{-17}	8.30	8.75	−0.37	−0.40	−13.88	−16.43
Shoulder	2.25×10^{-08}	7.90×10^{-16}	8.49	8.78	−0.37	−0.42	−17.46	−16.97
Calf	2.17×10^{-08}	5.48×10^{-13}	7.56	7.41	−0.36	−0.40	−16.73	−18.81
Wrist	5.63×10^{-05}	4.93×10^{-08}	6.06	5.58	−0.34	−0.26	−9.96	−22.79
Heel	2.97×10^{-04}	1.78×10^{-07}	5.69	5.32	−0.32	−0.25	−14.11	−19.22
Elbow	2.64×10^{-03}	1.07×10^{-05}	2.97	4.51	−0.23	−0.31	1.73	−13.62
Chest	1.96×10^{-02}	1.47×10^{-02}	−0.23	−2.10	0.00	0.22	17.21	22.96
Pelvic	3.33×10^{-02}	2.17×10^{-02}	1.05	2.15	−0.16	−0.32	−1.18	−23.34
Fibular	3.38×10^{-02}	2.45×10^{-02}	1.63	2.31	−0.28	−0.39	−5.57	−15.27
Shin	3.27×10^{-02}	3.04×10^{-02}	1.10	2.16	−0.17	−0.30	−7.61	−22.61
Upper arm–Forearm	5.14×10^{-02}	5.01×10^{-02}	−1.74	−2.05	0.35	0.43	1.09	40.49

Five Games before/after the injury.

Areas with significant impact: Very significant impacts on performance were observed in various areas, such as the ankle, knee, thigh, thoracolumbar, and foot areas.

- **Cohen's D and t-statistic:**
  - **Large Effect (>0.8)**: No areas fell under this category.
  - **Medium Effect (0.5–0.8)**: No areas with a medium effect size were identified.
  - **Small Effect (0.2–0.5)**: No areas with a small effect size were identified.
- **Percentage Change:**
  - **Most impacted:** The upper arm–forearm area was identified as the most impacted area based on the average percentage change, indicating a considerable decrease in performance post-injury.
  - **Least impacted:** The shin area was identified as the least impacted area, suggesting a relatively small decrease in performance.
- **Areas of Concern:**
  - Areas of concern with significant *p*-values but without a strong effect size included the ankle, knee, thigh, thoracolumbar, and foot areas, among others. These areas may require further attention due to this statistical significance.

Table 3. Five games before/after the injury.

Anatomical Sub-Areas	Avg. p-value	Median p-value	Avg. t-statistic	Median t-statistic	Avg. Cohen's D	Median Cohen's D	Average of Avg. % Change	Median Avg. % Change
Ankle	1.78×10^{-30}	7.46×10^{-74}	18.04	18.78	−0.35	−0.35	−4.88	−7.39
Knee	6.39×10^{-33}	6.94×10^{-52}	16.20	15.43	−0.28	−0.26	−1.56	−4.12
Thigh	4.32×10^{-22}	9.77×10^{-35}	12.73	12.70	−0.35	−0.34	−9.91	−12.09
Thoracolumbar	3.68×10^{-19}	2.37×10^{-25}	11.63	10.93	−0.30	−0.28	−3.27	−2.16
Foot	5.60×10^{-15}	3.04×10^{-24}	10.58	10.42	−0.35	−0.34	−3.33	−6.83
Abdominal	6.03×10^{-09}	2.79×10^{-20}	9.48	9.59	−0.42	−0.43	−8.54	−10.39
Shoulder	3.15×10^{-09}	1.49×10^{-19}	8.77	9.36	−0.36	−0.36	−4.78	−5.79
Hip	2.30×10^{-10}	4.40×10^{-17}	8.37	8.66	−0.35	−0.35	−3.70	−4.24
Calf	8.50×10^{-11}	5.00×10^{-14}	7.70	7.76	−0.34	−0.34	−7.96	−9.26
Hand–Thumb–Fingers	1.33×10^{-07}	8.27×10^{-13}	8.16	7.30	−0.35	−0.29	−5.57	−5.41
Wrist	2.60×10^{-06}	8.93×10^{-12}	7.01	7.07	−0.42	−0.43	−10.10	−9.99
Heel	6.18×10^{-06}	3.00×10^{-10}	6.41	6.48	−0.35	−0.35	−7.05	−8.92
Toes	5.40×10^{-05}	6.23×10^{-09}	6.03	6.01	−0.35	−0.33	−4.87	−2.27
Elbow	1.68×10^{-04}	1.51×10^{-05}	3.87	4.43	−0.28	−0.34	−3.50	−8.18
Chest	2.29×10^{-02}	4.40×10^{-03}	2.95	2.92	−0.29	−0.33	−3.32	−5.24
Shin	2.29×10^{-02}	6.91×10^{-03}	1.34	2.44	−0.18	−0.27	4.89	−1.10
Pelvic	3.07×10^{-02}	2.10×10^{-02}	1.89	2.42	−0.26	−0.29	−7.34	−16.70
Upper arm–Forearm	4.53×10^{-02}	4.15×10^{-02}	0.86	1.95	−0.10	−0.28	−10.80	−4.25
Fibular	4.47×10^{-02}	4.54×10^{-02}	1.69	2.08	−0.28	−0.35	0.90	4.41

Ten games before/after the injury.

Areas with significant impact: Very significant impacts on performance were noted in various areas, such as the ankle, knee, thigh, thoracolumbar, and foot areas, among others.

- **Cohen's D and t-statistic:**
  - **Large Effect (>0.8)**: No areas fell under this category.
  - **Medium Effect (0.5–0.8)**: No areas with a medium effect size were identified in the latest dataset.
  - **Small Effect (0.2–0.5)**: No areas with a small effect size are identified. This finding suggested that either the effect sizes were less than 0.2 or that the criteria for categorization may need adjustment based on the dataset specifics.
- **Percentage Change:**
  - **Most impacted:** The chest area is identified as the most impacted area based on the average percentage change, suggesting a notable decrease in performance metrics post-injury.
  - **Least impacted:** The upper arm–forearm area is identified as the least impacted area, which may suggest a relatively small change in performance.
- **Areas of Concern:**
  - Areas of concern with significant *p*-values but without a corresponding large or medium effect size included the ankle, knee, thigh, thoracolumbar, and foot areas, among several others.

Table 4. Ten games before/after the injury.

Anatomical Sub-Areas	Avg. p-value	Median p-value	Avg. t-statistic	Median t-statistic	Avg. Cohen's D	Median Cohen's D	Average of Avg. % Change	Median Avg. % Change
Ankle	2.05×10^{-41}	2.65×10^{-57}	16.19	16.34	−0.28	−0.26	−0.76	−3.83
Knee	8.79×10^{-42}	2.35×10^{-45}	15.91	14.37	−0.26	−0.22	3.17	3.43
Thigh	1.02×10^{-26}	2.86×10^{-29}	11.94	11.54	−0.31	−0.32	−2.42	−3.81
Thoracolumbar	2.35×10^{-26}	7.47×10^{-29}	12.01	11.39	−0.27	−0.27	3.05	2.45
Foot	2.34×10^{-15}	6.41×10^{-24}	10.49	10.36	−0.31	−0.31	1.18	−1.29
Abdominal	7.17×10^{-09}	6.73×10^{-18}	8.83	9.02	−0.35	−0.36	−3.63	−5.08
Shoulder	5.64×10^{-14}	5.82×10^{-14}	7.84	7.69	−0.29	−0.27	0.57	−1.47
Hip	3.97×10^{-11}	1.52×10^{-13}	7.58	7.56	−0.29	−0.27	5.20	1.55
Calf	3.12×10^{-10}	1.17×10^{-11}	7.19	6.95	−0.29	−0.25	0.57	0.54
Heel	2.07×10^{-07}	8.96×10^{-11}	6.85	6.69	−0.33	−0.33	−5.43	−5.25
Hand–Thumb–Fingers	1.10×10^{-08}	3.50×10^{-10}	7.11	6.67	−0.28	−0.26	1.49	0.68
Wrist	3.40×10^{-05}	1.43×10^{-09}	5.67	6.23	−0.33	−0.35	1.49	−2.68
Toes	1.33×10^{-05}	4.26×10^{-08}	5.72	5.76	−0.30	−0.27	−4.02	−5.09
Elbow	2.19×10^{-03}	2.15×10^{-06}	4.04	4.87	−0.26	−0.28	−1.98	−5.40
Chest	1.87×10^{-02}	1.02×10^{-03}	3.16	3.49	−0.32	−0.31	−49.15	−6.78
Pelvic	2.30×10^{-02}	1.39×10^{-02}	2.36	2.60	−0.26	−0.25	−8.06	−10.80
Fibular	3.22×10^{-02}	2.22×10^{-02}	2.37	2.42	−0.34	−0.36	−5.66	−6.96
Shin	3.13×10^{-02}	3.25×10^{-02}	2.22	2.18	−0.24	−0.23	4.53	2.28
Upper arm–Forearm	4.17×10^{-02}	4.12×10^{-02}	0.87	1.98	−0.11	−0.27	7.94	6.24

Tables 5–7 show the statistically significant results of the advanced performance metrics analyses, including test significance values, effect sizes, and average percentages of change in the 2-, 5-, and 10-game series **(RQ1)**.

Two games before/after the injury.

Notable Observations:

- Metrics such as POSS_ADVANCED, OFF_RATING_ADVANCED, DEF_RATING_ADVANCED, and others had average *p*-values less than 0.05, indicating significant impacts in these areas.
- **Cohen's D and t-statistic:**

- **Large Effect**: No metrics displayed a large effect size (Cohen's D > 0.8).
- **Medium Effect**: Metrics such as PLUS_MINUS_TRADITIONAL, PCT_BLK_USAGE, and BLK_TRADITIONAL had medium effect sizes (Cohen's D between 0.5 and 0.8).
- **Small Effect**: PCT_TOV_USAGE was the only metric with a small effect size (Cohen's D between 0.2 and 0.5).

- **Percentage Change:**
  - **Most Impacted:** DFGM_PLAYER_TRACK was the metric with the most significant average percentage change, indicating a considerable decrease in performance metrics post-injury.
  - **Least Impacted:** BLK_TRADITIONAL was the metric with the least average percentage change, suggesting a small change in performance.
- **Areas of Concern**: Metrics such as POSS_ADVANCED, OFF_RATING_ADVANCED, and DEF_RATING_ADVANCED had significant *p*-values with Cohen's D <= 0.2, which may indicate areas of concern despite their statistical significance.

Table 5. Two games before/after the injury—Basketball Performance Analytics.

Performance Metric	Median p-value	Avg. p-value	Avg. t-statistic	Median t-statistic	Median Cohen's D	Avg. Cohen's D	Median Avg. % Change	Average of Avg. % Change
POSS_ADVANCED	4.24×10^{-32}	4.24×10^{-32}	12.55	12.55	−0.53	−0.53	2.40	2.40
FG_PCT_PLAYER_TRACK	1.51×10^{-14}	1.51×10^{-14}	8.05	8.05	−0.54	−0.54	−15.97	−15.97
OFF_RATING_ADVANCED	2.32×10^{-07}	3.00×10^{-04}	7.13	6.82	−0.61	−0.62	−15.85	−15.51
DEF_RATING_ADVANCED	7.02×10^{-10}	6.34×10^{-04}	7.01	7.09	−0.58	−0.59	−14.09	−15.22
E_DEF_RATING_ADVANCED	1.04×10^{-02}	1.04×10^{-02}	2.79	2.79	−0.66	−0.66	−5.49	−5.49
OPP_FTA_RATE_FOUR_FACTORS	3.56×10^{-02}	3.56×10^{-02}	−2.24	−2.24	0.55	0.55	27.00	27.00
PCT_PF_USAGE	4.10×10^{-02}	4.10×10^{-02}	−2.18	−2.18	0.61	0.61	61.32	61.32
E_NET_RATING_ADVANCED	4.15×10^{-02}	4.15×10^{-02}	−2.16	−2.16	0.60	0.60	−183.09	−183.09
OPP_TOV_PCT_FOUR_FACTORS	4.95×10^{-02}	4.95×10^{-02}	−2.07	−2.07	0.65	0.65	27.79	27.79

Five games before/after the injury.

Metrics with significant impact: All the provided metrics had average *p*-values less than 0.05, indicating statistically significant impacts.

- **Cohen's D and t-statistic:**
  - **Large Effect**: None.
  - **Medium Effect (0.5–0.8)**: Metrics such as 'OPP_FTA_RATE_FOUR_FACTORS', 'PCT_PF_USAGE', 'E_NET_RATING_ADVANCED', and 'OPP_TOV_PCT_FOUR_FACTORS' fell into this category.
  - **Small Effect (0.2–0.5)**: No metrics fell into the small effect category.
- **Percentage Change:**
  - **Most impacted:** 'E_NET_RATING_ADVANCED' was the most impacted metric, with the highest median average percentage change.
  - **Notably Positive:** Metrics, including 'POSS_ADVANCED', 'OPP_FTA_RATE_FOUR_FACTORS', 'PCT_PF_USAGE', and 'OPP_TOV_PCT_FOUR_FACTORS' showed notably positive changes.
- **Metrics of Concern:** Metrics such as 'POSS_ADVANCED', 'FG_PCT_PLAYER_TRACK', 'OFF_RATING_ADVANCED', 'DEF_RATING_ADVANCED', and 'E_DEF_RATING_ADVANCED' were of concern due to their negative Cohen's D values.

Table 6. Five Games before/after the injury—Basketball Performance Analytics.

Performance Metric	*Median p-value*	*Avg. p-value*	*Avg. t-statistic*	*Median t-statistic*	*Median Cohen's D*	*Avg. Cohen's D*	*Median Avg. % Change*	*Average of Avg. % Change*
POSS_ADVANCED	4.24×10^{-32}	4.24×10^{-32}	12.55	12.55	−0.53	−0.53	2.40	2.40
FG_PCT_PLAYER_TRACK	1.51×10^{-14}	1.51×10^{-14}	8.05	8.05	−0.54	−0.54	−15.97	−15.97
OFF_RATING_ADVANCED	2.32×10^{-07}	3.00×10^{-04}	7.13	6.82	−0.61	−0.62	−15.85	−15.51
DEF_RATING_ADVANCED	7.02×10^{-10}	6.34×10^{-04}	7.01	7.09	−0.58	−0.59	−14.09	−15.22
E_DEF_RATING_ADVANCED	1.04×10^{-02}	1.04×10^{-02}	2.79	2.79	−0.66	−0.66	−5.49	−5.49
OPP_FTA_RATE_FOUR_FACTORS	3.56×10^{-02}	3.56×10^{-02}	−2.24	−2.24	0.55	0.55	27.00	27.00
PCT_PF_USAGE	4.10×10^{-02}	4.10×10^{-02}	−2.18	−2.18	0.61	0.61	61.32	61.32
E_NET_RATING_ADVANCED	4.15×10^{-02}	4.15×10^{-02}	−2.16	−2.16	0.60	0.60	−183.09	−183.09
OPP_TOV_PCT_FOUR_FACTORS	4.95×10^{-02}	4.95×10^{-02}	−2.07	−2.07	0.65	0.65	27.79	27.79

Ten games before/after the injury.

Metrics with significant impact: All the provided metrics had average *p*-values less than 0.05, indicating statistically significant impacts.

- **Cohen's D and t-statistic:**
  - **Large Effect (>0.8)**: None.
  - **Medium Effect (0.5–0.8)**: 'OPP_TOV_PCT_FOUR_FACTORS' and 'E_NET_RATING_ADVANCED' were identified in this category.
  - **Small Effect (0.2–0.5)**: Most of the other metrics fell into this category.
- **Percentage Change:**
  - **The most impacted genes,** 'OPP_TOV_PCT_FOUR_FACTORS' and 'E_NET_RATING_ADVANCED', were identified in this category.
  - **Notably Negative:** 'OPP_TOV_PCT_FOUR_FACTORS' and 'E_NET_RATING_ADVANCED' showed notable positive changes.
  - **Metrics of Concern:** Metrics such as 'OPP_PTS_FB_MISC', 'DEF_RATING_ADVANCED', 'OFF_RATING_ADVANCED', 'E_DEF_RATING_ADVANCED', 'POSS_ADVANCED', and 'OPP_EFG_PCT_FOUR_FACTORS' were of concern due to their negative Cohen's D values.

Table 7. Ten games before/after the injury—Basketball Performance Analytics.

Performance Metric	**Median p-value**	**Avg. p-value**	**Avg. t-statistic**	**Median t-statistic**	**Median Cohen's D**	**Avg. Cohen's D**	**Median Avg. % Change**	**Average of Avg. % Change**
OPP_PTS_FB_MISC	0.0005	0.0005	3.965	3.965	−0.650	−0.650	−11.830	−11.830
DEF_RATING_ADVANCED	0.0037	0.0034	5.640	3.111	−0.603	−0.647	−11.010	−11.610
OFF_RATING_ADVANCED	0.0051	0.0051	2.990	2.990	−0.538	−0.538	−10.590	−10.590
E_DEF_RATING_ADVANCED	0.0051	0.0051	3.092	3.092	−0.706	−0.706	−4.710	−4.710
POSS_ADVANCED	0.0091	0.0091	2.853	2.853	−0.543	−0.543	−11.230	−11.230
OPP_EFG_PCT_FOUR_FACTORS	0.0247	0.0247	2.404	2.404	−0.526	−0.526	−4.090	−4.090
OPP_TOV_PCT_FOUR_FACTORS	0.0264	0.0264	−2.372	−2.372	0.697	0.697	17.440	17.440
E_NET_RATING_ADVANCED	0.0446	0.0446	−2.125	−2.125	0.616	0.616	44.240	44.240

In sports, and more specifically in basketball which we examined through this research, understanding the intricate relationships between player injuries, their recovery time, and the resulting economic impact on teams is crucial. This understanding not only aids in better injury management but also in strategizing financial and team dynamics. To delve deeper into this aspect, our study presents two key tables—Tables 8 and 9—each serving a distinct yet interrelated purpose. Data revealed a significant correlation between the duration of player recovery and the financial implications for NBA teams, underscoring the critical nature of injury management and prevention in professional basketball.

The dataset analyzed in Table 8 encompassed a total of 30 unique teams to assess the average recovery time from injuries and quantify the total economic losses incurred by these teams as a result of these injuries. This table is instrumental in highlighting the broader impact of injuries across the league, offering insights into the average duration players take to recover and how this downtime translates into financial terms for their respective teams. The average recovery time for each team was calculated by summing the recovery periods for all injuries incurred by players on each team over the years studied, and then dividing this sum by the total number of injuries. To determine the total financial losses, we multiplied the per-game salary of each player by the number of games missed due to injury, and then aggregated these totals for each team, corresponding to the teams to which the respective players belonged over the years.

The average recovery time across all teams was approximately 35.98 days, with the total sum of team losses reaching USD 21,208,828,385.5. The team with the highest average recovery time was NOH–NOK–NOP (New Orlean Hornets and New Orleans Pelicans are the same teams with rebranding or relocation), at 48.19 days, which was correlated with a sum of team losses of USD 850,911,070.3. Conversely, the team with the lowest average recovery time was SAS (San Antonio Spurs), at 18.89 days, associated with a sum of team losses of USD 484,022,964.1 **(RQ4)**.

Table 8. Team recovery time correlated with the sum of losses in the period 2000 to 2023.

Teams	Average Recovery Time (2000–2023)	Sum of Losses (2000–2023)
GSW	38.33	USD 980,043,613.6
DEN	33.96	USD 898,608,370.5
WAS	42.38	USD 896,393,189.0
CLE	38.91	USD 884,262,820.6
NYK	43.09	USD 882,353,294.8
NOH–NOK –NOP [1]	47.13	USD 850,911,070.3
HOU	35.51	USD 831,909,820.5
LAL	43.89	USD 829,088,874.5
MEM–VAN [2]	37.27	USD 818,408,844.2
MIL	33.00	USD 803,077,829.5
BKN–NJN [3]	35.94	USD 787,297,893.7
POR	42.67	USD 725,597,473.1
TOR	37.21	USD 719,025,631.9
DAL	31.81	USD 717,319,559.4
IND	28.26	USD 707,021,308.5
MIA	27.46	USD 696,390,943.7
MIN	39.37	USD 687,081,943.9
CHA–CHH [4]	40.73	USD 672,569,410.7
LAC	32.64	USD 669,659,380.7
ORL	34.44	USD 650,059,655.1
PHI	29.59	USD 633,630,120.4
ATL	35.52	USD 629,062,649.4
CHI	41.94	USD 620,958,846.2
SAC	37.62	USD 593,901,503.1
PHX	37.92	USD 553,901,960.3
UTA	32.62	USD 552,960,349.6
DET	33.35	USD 494,764,653.5

SAS	21.36	USD 484,022,964.1
BOS	37.31	USD 470,742,686.1
OKC and SEA	29.40	USD 467,801,724.6
Grand Total	**35.98**	**USD 21,208,828,385.5**

[1] New Orleans Pelicans (previously the New Orleans Hornets, and before that, the Charlotte Hornets); [2] Memphis Grizzlies (The team started in Vancouver and moved to Memphis in 2001); [3] Brooklyn Nets (previously known as the New Jersey Nets until 2012); [4] Charlotte Hornets (The team was previously known as the Charlotte Bobcats).

Table 9, on the other hand, takes a more granular approach by breaking down injuries into specific anatomical sub-areas. It examines the average recovery time and associated economic losses for each type of injury, categorized by its location on the body. This detailed analysis is pivotal in understanding which injuries are most detrimental in terms of recovery time and economic burden, thereby guiding teams and healthcare professionals in prioritizing injury prevention and treatment strategies based on the anatomical area affected. It shows the average recovery time in days and the associated financial losses for different anatomical sub-areas affected by injuries within a sport context **(RQ2–4)**.

Table 9. Anatomical sub-area relationships with average recovery time and economic team losses.

Anatomical Sub-Areas	Avg. Recovery Time	Sum of Team Losses
Knee	44.47	USD 4,223,672,393.1
Unclassified	30.32	USD 3,923,783,660.9
Ankle	32.67	USD 2,509,238,498.5
Thigh	33.75	USD 1,544,221,395.7
Thoracolumbar	30.02	USD 1,345,058,412.9
Foot	43.91	USD 1,216,344,145.1
Hand–Thumb–Fingers	51.29	USD 1,025,316,589.5
Heel	45.94	USD 718,869,461.3
Shoulder	47.04	USD 691,206,599.1
Abdominal	35.21	USD 630,757,817.8
Calf	36.75	USD 595,174,649.9
Hip	28.63	USD 480,523,199.1
Wrist	46.31	USD 412,959,249.0
Cranial	32.92	USD 269,506,780.6
Toes	40.45	USD 225,354,084.5
Elbow	48.64	USD 220,358,271.9
Rest	11.59	USD 190,999,755.3
Other facial areas	64.23	USD 143,326,062.1
Neck	20.94	USD 138,930,281.6
Shin	44.00	USD 115,452,588.8
Digestive	13.02	USD 107,701,146.1
Mouth	25.98	USD 90,712,536.9
Eye	36.47	USD 79,136,024.3
Fibular	75.04	USD 64,233,781.7
Nose	21.17	USD 54,995,090.5
Pelvic	30.78	USD 53,377,027.9
Chest	16.39	USD 42,115,533.9
COVID-19-related	76.44	USD 32,549,095.0
Upper arm–Forearm	43.45	USD 32,083,939.4
Respiratory	19.80	USD 30,870,312.7

	USD 21,208,828,385.1

The data encompassed a range of anatomical sub-areas with varying average recovery times and sums of team losses. The area with the longest average recovery time was the hand–thumb–fingers area at 51.29 days, coinciding with a financial impact of USD 1,025,316,589.5. In contrast, the digestive area had the shortest recovery time at 13.02 days, with associated losses of USD 107,701,146.1.

The knee area had the highest financial burden at USD 4,223,672,393.1, aligning with a significant recovery time of 44.47 days. Respiratory issues, despite having a low average recovery time of 19.80 days, had a disproportionately high financial impact of USD 30,870,312.7, which could reflect the broader implications of respiratory problems on player health and availability. The total sum of team losses across all anatomical sub-areas was substantial, amounting to USD 21,208,828,385.1 for the period from 2000 to 2023.

Tables 10–12 provide a breakdown of injuries categorized by anatomical sub-areas with further classification into defensive, miscellaneous, offensive, and rating injury categories. The Grand Total represents the sum of all these categories for each anatomical area. Tables 10–12 are based on the proper categorization of Table A1 to achieve more focused analysis. Our filtered data analysis revealed a distribution of injuries across various anatomical sub-areas, with an emphasis on the effect size and significance of each injury. Table A1 shows the categorization of basketball performance analytics (defensive, miscellaneous, offensive, and rating). Rating metrics provide a high-level view of a player's overall impact. Offensive and defensive metrics break down the specifics of how points are scored and prevented and what efficiencies exist in various facets of the game. The miscellaneous category offers additional context and insights into the nuances of gameplay, such as fast break effectiveness or how players indirectly contribute to scoring (**RQ3**).

In the analyses shown in Table 10, we examined the incidence of anatomical sub-area injuries across different performance analytics categories: miscellaneous (Misc), offensive, and defensive plays, in addition to the ratings of these injuries. Our dataset spanned two game seasons and included injuries related to COVID-19. The pelvic area exhibited the greatest number of statistically significant effects on performance (11), with the majority falling under the defensive category (3). Interestingly, COVID-19-related issues were notable, with a total of nine occurrences, indicating a significant impact on player availability. The wrist and abdominal areas were also common injury sites, with seven and eight incidences, respectively. Defensive play was associated with the highest number of injuries (24), followed by offensive play (16) and miscellaneous causes (8).

Table 10. Anatomical sub-area injuries compared between performance analytics categories (defensive, miscellaneous, offensive, and rating) based on test significance and effect size for the two-game series before and after injury.

Anatomical Sub-areas (2d)	*Rating*	*Misc*	*Offensive*	*Defensive*	*Grand Total*
Abdominal	4	1	1	2	8
Ankle			1	1	2
Calf			1	1	2
Chest			1	1	2
COVID-19-related	4	2	1	2	9
Cranial			1	1	2
Elbow				1	1
Eye				1	1
Fibular			3	1	4
Foot				1	1
Hand–Thumb–Fingers			1	1	2
Heel	1			1	2

Hip			1	1	2
Mouth	2				2
Pelvic	4	3	1	3	11
Shin			1	1	2
Shoulder			1	1	2
Thigh			1	1	2
Toes				1	1
Upper arm–Forearm	1	1		1	3
Wrist	4	1	1	1	7
Grand Total	**20**	**8**	**16**	**24**	**68**

The analysis of anatomical sub-area injuries across a five-game series (Table 11) indicated that a total of 22 statistically significant effects were associated with performance variation. Defensive plays accounted for the highest number of injuries (11), suggesting a greater risk for this play type. The upper arm–forearm area, along with the abdominal area, had the highest number of injuries recorded (three each), reflecting their vulnerability or exposure during gameplay. COVID-19-related instances were recorded (two), but their impact was less pronounced than that of other injury types. Notably, only five injuries were rated, with the rest not specified for severity.

Table 11. Anatomical sub-area injuries compared between performance analytics categories (defensive, miscellaneous, offensive, and rating) based on test significance and effect size for the five-game series before and after injury.

Anatomical sub-areas (5d)	***Rating***	***Misc***	***Offensive***	***Defensive***	***Grand Total***
Abdominal	1		1	1	3
Chest			1	1	2
COVID-19-related	1	1			2
Elbow				1	1
Hand–Thumb–Fingers				1	1
Heel				1	1
Other facial areas				1	1
Pelvic			1	1	2
Toes				1	1
Upper arm–Forearm	3			2	5
Wrist		1	1	1	3
Grand Total	**5**	**2**	**4**	**11**	**22**

As shown in Table 12, over the course of ten games, our analysis revealed a total of 11 statistically significant effects on performance across four anatomical sub-areas. The upper arm–forearm area had the highest incidence of injuries, with a total of six injuries, four of which were rated for their impact. Defensive plays were again highlighted as the most common scenario for injuries, with a total of four occurrences. Injuries in other areas were less frequent, with the fibular and pelvic areas each reporting two cases and the abdominal area reporting one. Only one injury was attributed to offensive play, and one was categorized as miscellaneous.

Table 12. Anatomical sub-area injuries compared between performance analytics categorization (defensive, miscellaneous, offensive, and rating) based on test significance and effect size for the ten-game series before and after injury.

Anatomical sub-areas (10d)	**Rating**	**Offensive**	**Misc**	**Defensive**	**Grand Total**
Upper arm–Forearm	4			2	6
Fibular	1		1		2
Abdominal				1	1

Pelvic		1		1	2
Grand Total	**5**	**1**	**1**	**4**	**11**

4. Discussion

Cohen's D provides a standardized metric of the difference between two means in terms of standard deviations, making it easier to understand the magnitude of the difference. On the other hand, t-test tests determine whether the difference is statistically significant. A large t-statistic often indicates a large effect size (although the relationship is not strictly linear due to the square root in the denominator) **(RQ1)**.

According to the Results section, one of the aims of the paper is to identify the patterns and relationships of anatomical sub-areas and advanced performance metrics in game series in two-, five-, and ten-game series. In each case, the analysis has shown the following:

For two games before/after the injury.
Inconclusive Areas:

- Inconclusive areas, such as the ankle, knee, and thigh areas, included those with significant *p*-values but were not the most or least impacted.
- **Notable Observations.**
- **The Negative Cohen's D**, many areas, including the ankle, knee, and thigh areas, had negative Cohen's D values, suggesting a decrease in performance post-injury across these areas.
- **Contrast Areas:** There are no areas that had a positive average Cohen's D but a significant *p*-value, which suggests that all significant areas had a negative impact on performance.
- **Percentage Change Insight:** Many areas showed a negative average percentage change, indicating a decrease in performance post-injury. The significant areas with a negative change in performance cover a broad range, from the ankle area to the respiratory area, suggesting widespread impacts of injuries.

For five games before/after the injury.
Inconclusive Areas:

- Inconclusive areas with significant *p*-values that were neither most nor least impacted included the ankle, knee, thigh, thoracolumbar, foot, abdominal, and other areas. These areas exhibited significant statistical findings but did not show the extremities of impact, warranting a more nuanced interpretation.

Notable Observations.

- **Negative Cohen's D**: Several areas showed a negative Cohen's D, suggesting that injuries in these areas, such as the ankle, knee, and thigh areas and several others, generally lead to a decrease in performance post-injury.
- **Percentage Change Insight**: The analysis showed that most of the significant areas had a negative average percentage change, indicating a general decrease in performance post-injury across various anatomical sub-areas.

For ten games before/after the injury.
Inconclusive Areas:

- Inconclusive areas with significant *p*-values that were neither most nor least impacted included the ankle, knee, thigh, thoracolumbar, foot, abdominal, and other areas. The impact in these areas is significant but does not show extremes, which could warrant further investigation or a more detailed analysis.

Notable Observations.

- **Negative Cohen's D**: Several areas exhibited a negative Cohen's D, indicating a general trend toward decreased performance post-injury. This includes the ankle, knee, thigh, thoracolumbar, foot, and additional areas.

- **Percentage Change Insight**: A range of areas showed a negative average percentage change, denoting a decrease in performance post-injury. These included the ankle, thigh, abdominal, heel, toes, elbow, chest, pelvic, and fibular areas.

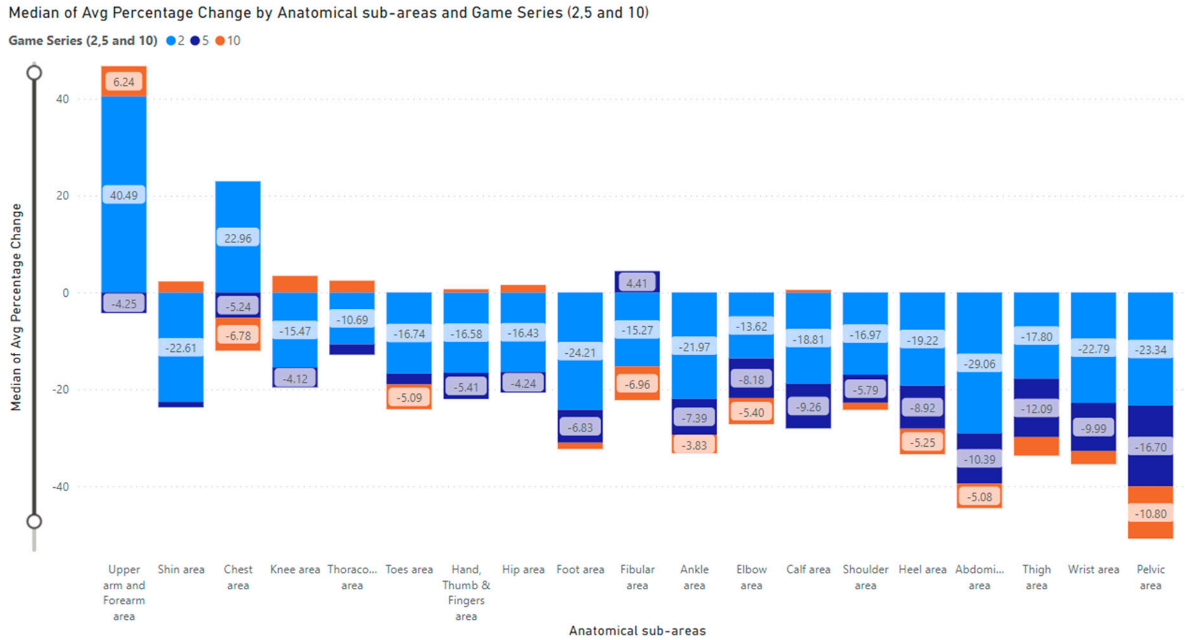

Figure 2. Comparison of two-, five-, and ten-game series in median % change of anatomical sub-areas.

The matrix below (Table 13) and Figure 2 (bar chart that compares the percentage change of the anatomical sub-areas) above offers a comparative analysis of the performance impact before and after injury events across two-, five-, and ten-game series. We have structured our findings around key metrics: areas with significant impact, effect size based on Cohen's D, percentage change in performance, and highlighted areas of concern. This approach provides a comprehensive view of how injuries affect player performance across different games, enabling us to pinpoint specific areas that require attention and possible intervention (**RQ1**).

Table 13. Comparison matrix of Anatomical sub-areas for all the game series (two, five, and ten).

Metrics-Dimensions	2 Games	5 Games	10 Games
Areas with Significant Impact on Concern	Abdominal, Foot, Pelvic	Pelvic, Thigh, Abdominal	Pelvic, Chest, Ankle
% Change	**Most Impacted**: Abdominal area (−29.06%); **Least Impacted**: Upper Forearm area (40.49%)	**Most Impacted**: Pelvic area (−16.70%); **Least Impacted**: Fibular area (4.41%)	**Most Impacted**: Pelvic area (−10.80%); **Least Impacted**: Upper arm–Forearm area (6.24%)

For two games before/after the injury—Basketball Performance Analytics. Notable Observations.

- **Negative Cohen's D**: Not explicitly listed; however, metrics with a negative Cohen's D indicate a decrease in performance post-injury.
- **Percentage Change Insight**: The most significant percentage change was found for DFGM_PLAYER_TRACK, with a change of −71.23%, and the least significant change was a 65.15% change for BLK_TRADITIONAL. This insight highlights the metrics that have undergone the most and least changes in terms of performance.

For five games before/after the injury—Basketball Performance Analytics.
Notable Observations.

- **Negative Cohen's D**: A significant number of performance metrics had negative values for Cohen's D, indicating that, on average, post-injury performance tends to be lower than pre-injury performance.
- **Percentage Change Insight:** 'PCT_PF_USAGE' stands out as the most impacted metric. The highest positive change observed was 61.32% (in 'PCT_PF_USAGE'). The most significant negative change was −183.09% (in 'E_NET_RATING_ADVANCED').

For ten games before/after the injury—Basketball Performance Analytics.
Notable Observations.

- **Negative Cohen's D**: The same metrics listed as 'Metrics of Concern' also feature here, indicating their potential negative impact.
- **Percentage Change Insight:** 'E_NET_RATING_ADVANCED' was the most impacted metric, with the highest positive change of 44.24%. The most significant negative change was −11.83% in 'OPP_PTS_FB_MISC'.

The matrix in Table 14 and Figure 3 (bar chart comparison of the performance metrics median percentage change for two-, five-, and ten-game series) consolidate the information from the previous analyses. The "Most Impacted" column focuses on the largest negative impact, while the "Least Impacted/Notably Positive" column emphasizes metrics that either showed minor declines or demonstrated potential positive changes post-injury. The "Metrics of Concern" column underscores the metrics that exhibited notable declines in performance, which might be areas to prioritize in future analyses or interventions.

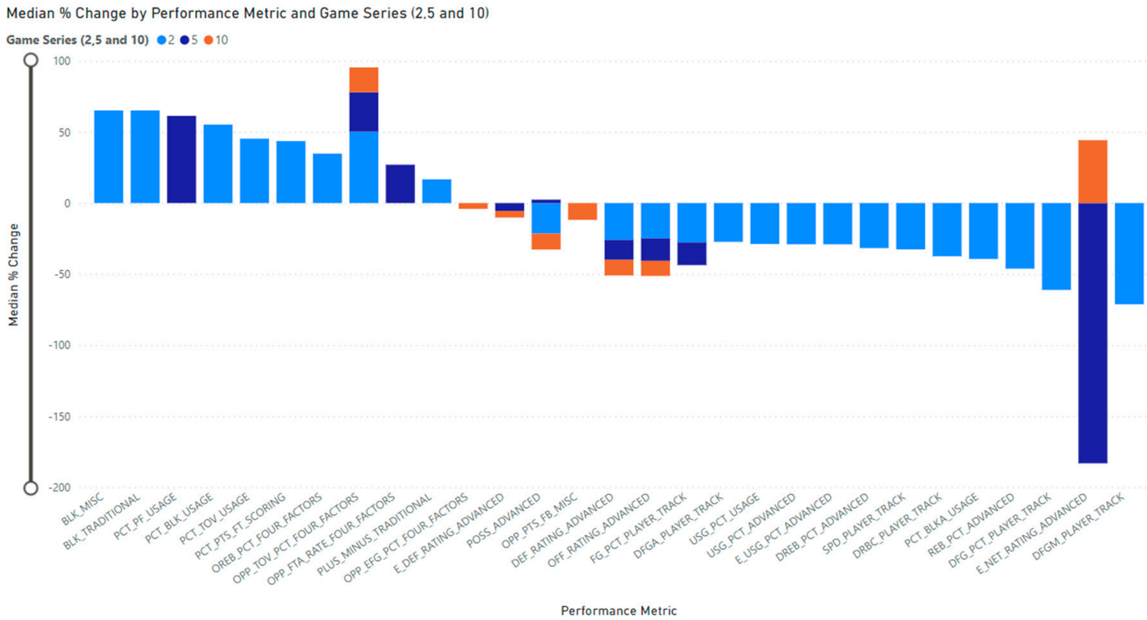

Figure 3. Comparison of two-, five-, and ten-game series for median % change of performance metrics.

The data present the relationship between recovery time and team losses. Several hypotheses could be posited as follows (**RQ2–4**):

1. **Team Performance**: Longer recovery times could either indicate a more thorough recovery protocol, potentially leading to better long-term team performance, or could be a sign of more severe injuries. The data alone do not clarify this relationship.
2. **Economic Impact**: An injury's economic impact (sum of team losses) does not have a clear connection with recovery time. This could be due to a multitude of factors not

accounted for in this dataset, such as the nature of the sport, insurance policies, revenue streams of each team, or the impact of star players' injuries.

Table 14. Comparison matrix of the performance metrics for all the game series (2, 5 and 10).

Metric/Dimension	2 Games	5 Games	10 Games
Significant Impact	All metrics have p-values below 0.05	All metrics have p-values below 0.05	All metrics have p-values below 0.05
Cohen's D	PCT_TOV_USAGE, PLUS_MINUS_TRADITIONAL, PCT_BLK_USAGE, BLK_TRADITIONAL, BLK_MISC, PCT_PTS_FT_SCORING, OPP_TOV_PCT_FOUR_FACTORS, OREB_PCT_FOUR_FACTORS	OPP_FTA_RATE_FOUR_FACTORS, PCT_PF_USAGE, E_NET_RATING_ADVANCED, OPP_TOV_PCT_FOUR_FACTORS	OPP_TOV_PCT_FOUR_FACTORS, E_NET_RATING_ADVANCED
% Change	Most impacted: +65.15% in BLK_TRADITIONAL; Least impacted: −71.23% in DFGM_PLAYER_TRACK	Most impacted: +61.32% in PCT_PF_USAGE; Least impacted: −183.09% in E_NET_RATING_ADVANCED	Most impacted: +44.24% in E_NET_RATING_ADVANCED; Least impacted: −11.83% in OPP_PTS_FB_MISC
Areas of Concern	DEF_RATING_ADVANCED with the highest average % decline	DEF_RATING_ADVANCED showing a continued decline	Multiple metrics with both positive and negative changes; care needed in interpretation

The variation in recovery times and financial losses across anatomical sub-areas could be indicative of several underlying factors **(RQ2 and RQ4)**:

1. **Frequency of Injuries**: Certain areas, such as the hand–thumb–finger and knee areas, may be more prone to injuries that are both severe and frequent, leading to longer recovery times and higher costs.
2. **Economic Impact**: This variable is proportional to recovery time, which suggests that some injuries, even those that are less frequent or have shorter recovery times, may still incur significant costs. This could be due to factors such as the player's position, the importance of the player to the team, or medical expenses specific to certain types of injuries.
3. **Implications for Player Health**: Respiratory issues, while having a shorter average recovery time, have a high financial impact, possibly due to the COVID-19 pandemic's effects, as shown by the separate listing of COVID-19 with a very high recovery time (76.44 days) and associated costs.

The data indicate a variance in injury occurrence according to anatomical sub-area, with some regions being more prone to injury in certain contexts (defensive vs. offensive play) than others **(RQ3)**.

1. Injury distribution: A greater frequency of injuries in the pelvic and fibular areas might indicate that these regions are either more vulnerable during play or that the nature of the sport involves more activities that put these areas at risk.
2. Contextual Classification: The predominance of injuries in the miscellaneous category could suggest either a wide variety of other non-classifiable injuries or a potential issue with the classification system itself.
3. Offensive vs. Defensive Injuries: The data might reflect the different types of stresses placed on the body during offensive and defensive plays, with certain areas being more affected by offensive maneuvers and others by defensive actions.

4. Implications for Prevention and Treatment: Understanding which anatomical areas are most at risk and in which context can help in developing targeted injury prevention and rehabilitation programs.

Table 15 synthesizes the results of Tables 10–12 injuries across the three types of game series (two, five, and ten games) to highlight trends in physical injuries within different anatomical sub-areas and types of play. This study offers insights into the recurrent nature of certain injuries and informs targeted preventative strategies **(RQ1)**.

Table 15. Comparison of injuries in the different game series.

Aspect	Two-game Series	Five-game Series	Ten-game Series
Injury Prone Areas	Pelvic and wrist areas had notable injury incidences.	Shift in high incidence of injuries to the upper arm–forearm area.	Upper arm–forearm area remained most prone to injuries.
Play Type Risks	Defensive plays associated with the highest number of injuries.	Defensive injuries continued to be significant, reflective of the physical demands of the sport.	Defensive play injuries persisted, emphasizing the need for focused preventative strategies.
Injury Ratings	Some injuries rated, but without a high severity in any specific area.	Ratings not extensively reported, suggesting a need for more detailed injury impact assessments.	Ratings more prevalent, especially in the upper arm–forearm area, indicating higher risk.

5. Conclusions and Future Work

The anatomical impact assessment showed consistent involvement of the knee, ankle, and thigh areas across all of the game series, suggesting that these may be critical areas for athletic performance or injury prevention. In terms of the performance metrics, all of the selected metrics consistently demonstrated statistical significance, with *p*-values less than 0.05, indicating that these metrics were significantly different across games. Notably, the percentage changes in metrics, such as 'BLK_TRADITIONAL' in game two and 'PCT_PF_USAGE' in game five, exhibited substantial positive changes, while 'E_NET_RATING_ADVANCED' demonstrated the most significant negative change in game five and most positive change in game ten series, indicating a possible area of volatility or targeted improvement. Interestingly, 'DEF_RATING_ADVANCED' exhibited a persistent decrease in expression, warranting further investigation. These findings underscore the importance of continuous monitoring and analysis of both anatomical and performance metrics to optimize athlete performance and well-being over time. **(RQ1)**.

Although we analyzed the range of recovery times and the total sum of team losses, the analysis does not offer a straightforward interpretation of the relationship between these variables. Future research should aim to incorporate additional data points, such as the severity of injuries, the number of players affected, the financial structure of each team, the particular sport in question, and any insurance compensation received.

Moreover, understanding the context of the losses—whether they pertain to missed games, decreased ticket sales, or other factors—is crucial for a more comprehensive analysis. Finally, longitudinal studies tracking these variables over multiple seasons could provide insights into whether the observed patterns are consistent and whether recovery times have a direct or indirect impact on the financial outcomes of sports teams. It would also be beneficial to include performance metrics post-recovery to evaluate the effectiveness of recovery time on player performance **(RQ1–4)**.

The analysis revealed significant disparities in recovery times and financial impacts across different anatomical sub-areas. Although some injuries may require longer healing, others may have a greater economic impact regardless of recovery duration. Recovery time does not necessarily correlate directly with financial impact, highlighting the complex nature of sports injuries and their consequences. These data underscore the importance of targeted injury prevention and management strategies for different anatomical sub-areas. Financial implications of injuries extend beyond direct healthcare costs and can significantly affect a team's finances. For a more comprehensive understanding, further research should incorporate additional variables, such as the frequency of injuries per anatomical area, the average contract value of injured players, and the timeline of injuries in relation to the sports season. Additionally, a more in-depth analysis might consider the role of player insurance policies and the effect of player absence on team performance and revenue streams **(RQ2–4)**.

The analysis of the injury distribution across anatomical sub-areas reveals significant differences in the frequency of injuries associated with defensive and offensive actions, as well as other non-specified (Misc) activities. Certain anatomical areas, particularly the pelvic and fibular areas, are more susceptible to injury, emphasizing the need for focused prevention strategies. The large number of 'Misc' injuries suggests a diversity of incidents that occur outside of standard defensive or offensive plays, highlighting the multifaceted nature of sports injuries. The rating data are not directly interpretable without further context, but a high score might be indicative of more severe or costly injuries. To further this research, it would be beneficial to integrate these data with other datasets that provide additional context, such as the type of sport, level of play, condition of the player, and other potential risk factors. Additionally, qualitative data regarding the circumstances of each injury could provide insights into the causal factors and help tailor preventative measures more effectively **(RQ3)**.

Throughout the three examined game series, the data consistently highlighted the upper arm–forearm area as the most injury prone, suggesting a critical focus for prevention and protection efforts. The persistently high risk associated with defensive plays calls for specialized training and potentially revised play strategies to mitigate injury risks. The evolving understanding of injury severity through more frequent ratings by the tenth game in a series provides valuable insights into the areas requiring the most immediate attention. Overall, the conclusions emphasize the necessity of continuous improvement in player safety measures, which should be informed by an ever-growing and precise body of performance analytics data **(RQ1 and RQ3)**.

Sports injuries, beyond their immediate physical toll, cascade into realms of performance and economics in basketball. Recognizing these nuances can empower stakeholders—from medical staff to team management—to strategize injury management, optimize player welfare, and formulate robust team strategies.

Author Contributions: Conceptualization: V.S.; methodology: V.S. and G.P.; software: V.S. and G.P.; validation: CT, V.S. and G.P.; formal analysis: V.S. and G.P.; investigation: V.S. and G.P.; resources: C.T., V.S. and G.P.; data curation: V.S. and G.P.; writing—original draft preparation: V.S.; writing—review and editing: C.T., V.S. and G.P.; visualization: V.S.; supervision: C.T; project administration: C.T. and V.S.; funding acquisition, (not applicable). All authors have read and agreed to the published version of the manuscript.

Funding: This research is co-financed by Greece and the European Union (European Social Fund-SF) through the Operational Programme "Human Resources Development, Education and Lifelong Learning 2014-2020" in the context of the project "Support for International Actions of the International Hellenic University", (MIS 5154651).

Data Availability Statement: All data were contained in the main text.

Conflicts of Interest: The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. This manuscript complies with ethical standards.

Appendix A

Table A1 displays the categorization of basketball performance metrics into four main areas: rating, Misc, offensive, and defensive. Each area contains various basketball performance analytics for players and teams. In more detail, each performance category analyses:

1. **Rating**: Measures overall player efficiency and impact on the game. Advanced metrics that normalize performance to account for pace and playing time, such as NET_RATING_ADVANCED and PACE_PER40_ADVANCED, are included. Usage percentages such as USG_PCT highlight a player's involvement in game plays.
2. **Offensive**: Quantifies scoring, playmaking, and efficiency of the offense. Traditional statistics such as FGM and FGA track shot-making, whereas advanced statistics such as OFF_RATING_ADVANCED measure offensive efficiency. Scoring percentages associated with specific play types, such as PCT_PTS_2PT_SCORING or PCT_PTS_3PT_SCORING, indicate where a player or team excels in scoring.
3. **Defensive**: Evaluates a player's or team's defensive effectiveness. DREB_PCT_ADVANCED could indicate a player's ability to rebound on the defensive end. Steal-related statistics such as STL_TRADITIONAL and PCT_STL_USAGE measure defensive playmaking.
4. **Miscellaneous**: Captures diverse aspects of the game not strictly classified as offensive or defensive. PTS_FB_MISC and PTS_PAINT_MISC provide insight into how teams score in transition and in the paint. Player-tracking data, as indicated by metrics with "_PLAYER_TRACK", offer a detailed look into player movements and actions. PFD_MISC and SAST_PLAYER_TRACK can indicate a player's influence on the game beyond primary scoring and assists.

Table A1. Rating, Misc, Offensive and Defensive categorization of the Basketball Performance Analytics.

Rating	Misc	Offensive	Defensive
AST_PCT_ADVANCED: Percentage of team field goals a player assisted while on court	BLK_MISC: Miscellaneous block statistics not fitting traditional or advanced categories	AST_TRADITIONAL: Traditional count of assists made by a player.	DREB_PCT_ADVANCED: Advanced metric measuring the percentage of available defensive rebounds a player grabbed while on the court.
AST_RATIO_ADVANCED: Assists per 100 possessions used by a player	BLKA_MISC: Miscellaneous statistics for shots blocked by opponents	E_OFF_RATING_ADVANCED: Advanced metric evaluating a player or team's offensive efficiency.	DEF_RATING_ADVANCED: An advanced metric that estimates a player's overall defensive impact per 100 possessions.
AST_TOV_ADVANCED: Ratio of a player's assists to turnovers	OPP_PTS_2ND_CHANCE_MISC: Points scored by opponents on second-chance opportunities	FG_PCT_TRADITIONAL: Traditional field goal percentage, measuring overall shooting success.	DREB_TRADITIONAL: Traditional count of defensive rebounds grabbed by a player.
E_NET_RATING_ADVANCED: Player's net impact on team's offensive and defensive efficiency	OPP_PTS_FB_MISC: Points scored by opponents on fast breaks	FG3_PCT_TRADITIONAL: Traditional three-point field goal percentage.	E_DEF_RATING_ADVANCED: Enhanced defensive rating, offering a more comprehensive view of a player's defensive efficiency.
E_PACE_ADVANCED: Estimate of the pace at which a player plays (possessions per 48 min)	OPP_PTS_OFF_TOV_MISC: Points scored by opponents off turnovers	FG3A_TRADITIONAL: Traditional count of three-point field goal attempts by a player.	BLK_TRADITIONAL: Traditional count of shots blocked by a player.
E_USG_PCT_ADVANCED: Usage rate, measuring the percentage of team plays involving a player while on court	OPP_PTS_PAINT_MISC: Points scored by opponents in the paint	FG3M_TRADITIONAL: Traditional count of three-point field goals made.	REB_PCT_ADVANCED: Advanced metric measuring the percentage of total rebounds (offensive and defensive) a player grabbed while on the court.
EFG_PCT_ADVANCED: Effective field goal percentage, accounting for 3-point field goals	PF_MISC: Personal fouls count in miscellaneous situations	FGA_TRADITIONAL: Traditional count of total field goal attempts.	REB_TRADITIONAL: Traditional count of total rebounds (both offensive and defensive) grabbed by a player.
EFG_PCT_FOUR_FACTORS: Part of the 'Four Factors' of basketball success, measuring effective shooting efficiency	PFD_MISC: Count of personal fouls drawn in various scenarios	FGM_TRADITIONAL: Traditional count of total field goals made.	STL_TRADITIONAL: Traditional count of steals made by a player.
FTA_RATE_FOUR_FACTORS: Free-throw attempt rate in the context of the 'Four Factors'	PTS_2ND_CHANCE_MISC: Points scored on second-chance opportunities	FT_PCT_TRADITIONAL: Traditional free-throw percentage.	PCT_STL_USAGE: Percentage of a player's steals relative to their overall on-court engagement and usage.

FTA_TRADITIONAL: Traditional count of a player’s free-throw attempts	PTS_FB_MISC: Points scored on fast breaks	OFF_RATING_ADVANCED: Advanced metric for assessing a player’s or team’s offensive performance per 100 possessions.
FTM_TRADITIONAL: Traditional count of a player’s successful free throws	PTS_OFF_TOV_MISC: Points scored off turnovers	OREB_PCT_ADVANCED: Advanced metric measuring the percentage of available offensive rebounds a player grabbed while on the court.
MIN_ADVANCED: Minutes played, an advanced metric considering various factors	PTS_PAINT_MISC: Points scored in the paint	OREB_PCT_FOUR_FACTORS: Offensive rebound percentage as part of the ‘Four Factors’ in basketball analysis.
NET_RATING_ADVANCED: Team’s point differential per 100 possessions while the player is on the court	AST_PLAYER_TRACK: Assists tracked in specific player tracking scenarios	OREB_TRADITIONAL: Traditional count of offensive rebounds grabbed by a player.
OPP_EFG_PCT_FOUR_FACTORS: Opponent’s effective field goal percentage, a defensive metric	CFG_PCT_PLAYER_TRACK: Player’s catch-and-shoot field goal percentage in player tracking	PCT_AST_2PM_SCORING: Percentage of two-point field goals made that were assisted.
OPP_FTA_RATE_FOUR_FACTORS: Opponent’s free-throw attempt rate, indicating defensive efficiency	CFGA_PLAYER_TRACK: Player’s catch-and-shoot field goal attempts in player tracking	PCT_AST_3PM_SCORING: Percentage of three-point field goals made that were assisted.
OPP_OREB_PCT_FOUR_FACTORS: Opponent’s offensive rebound percentage, a defensive metric	CFGM_PLAYER_TRACK: Player’s catch-and-shoot field goals made in player tracking	PCT_AST_FGM_SCORING: Overall percentage of field goals made that were assisted.
OPP_TOV_PCT_FOUR_FACTORS: Opponent’s turnover percentage, a part of defensive metrics	DFG_PCT_PLAYER_TRACK: Player’s defense against field goal percentage in player tracking	PCT_PTS_2PT_MR_SCORING: Percentage of points scored from mid-range two-point shots.
PACE_ADVANCED: The pace factor, estimating the number of possessions per 48 min	DFGA_PLAYER_TRACK: Player’s defense against field goal attempts in player tracking	PCT_PTS_2PT_SCORING: Percentage of points scored from all two-point field goals.
PACE_PER40_ADVANCED: Similar to pace factor but calculated per 40 min	DFGM_PLAYER_TRACK: Player’s defense against field goals made in player tracking	PCT_PTS_3PT_SCORING: Percentage of points scored from three-point field goals.
PCT_AST_USAGE: Percentage of team’s assists for which a player accounts while playing	FTAST_PLAYER_TRACK: Free-throw assists tracked in player tracking scenarios	PCT_PTS_PAINT_SCORING: Percentage of points scored in the paint.
PCT_BLK_USAGE: Percentage of team’s blocks for which a player accounts while playing	ORBC_PLAYER_TRACK: Offensive rebounds captured in player tracking	PCT_UAST_2PM_SCORING: Percentage of two-point field goals made without an assist.
PCT_BLKA_USAGE: Percentage of a player’s shots that are blocked by opponents	PASS_PLAYER_TRACK: Passes made tracked in player tracking scenarios	PCT_UAST_3PM_SCORING: Percentage of three-point field goals made without an assist.
PCT_DREB_USAGE: Percentage of available defensive rebounds a player gets	RBC_PLAYER_TRACK: Rebounds captured in player tracking	PCT_UAST_FGM_SCORING: Overall percentage of field goals made without an assist.
PCT_FG3A_USAGE: Percentage of a team’s three-point attempts taken by a player	SAST_PLAYER_TRACK: Secondary assists tracked in player-tracking scenarios	PCT_FGA_2PT_SCORING: Percentage of total field goal attempts that are two-point shots.
PCT_FG3M_USAGE: Percentage of a team’s three-point makes attributed to a player	SPD_PLAYER_TRACK: Speed of the player during play, tracked in player-tracking scenarios	PCT_FGA_3PT_SCORING: Percentage of total field goal attempts that are three-point shots.
PCT_FGA_USAGE: Percentage of team’s field goal attempts taken by a player	TCHS_PLAYER_TRACK: Touches of the ball by the player tracked in player tracking	PTS_TRADITIONAL: Traditional count of total points scored by a player.
PCT_FGM_USAGE: Percentage of team’s field goals made by a player	UFG_PCT_PLAYER_TRACK: Player’s unguarded field goal percentage in player tracking	PCT_OREB_USAGE: Percentage of team’s offensive rebounds a player accounts for while on the court.

PCT_FTA_USAGE: Percentage of team's free-throw attempts taken by a player	UFGA_PLAYER_TRACK: Player's unguarded field goal attempts in player tracking	PCT_PTS_USAGE: Percentage of team's points for which a player accounts while on the court.
PCT_FTM_USAGE: Percentage of team's free throws made by a player	UFGM_PLAYER_TRACK: Player's unguarded field goals made in player tracking	PCT_PTS_FB_SCORING: Percentage of points scored from fast breaks.
PCT_REB_USAGE: Percentage of team's total rebounds grabbed by a player	PCT_TOV_USAGE: Percentage of a player's turnovers relative to their usage rate	PCT_PTS_FT_SCORING: Percentage of points scored from free throws.
PIE_ADVANCED: Player Impact Estimate, a measure of a player's overall statistical contribution	DIST_PLAYER_TRACK: Distance covered by the player during play, tracked in player tracking	PCT_PTS_OFF_TOV_SCORING: Percentage of points scored off turnovers.
PLUS_MINUS_TRADITIONAL: The point differential when the player is on and off the court	DRBC_PLAYER_TRACK: Defensive rebounds captured in player tracking	
POSS_ADVANCED: The number of possessions a player is involved in	FG_PCT_PLAYER_TRACK: Player's overall field goal percentage in player tracking	
TM_TOV_PCT_ADVANCED: Team's turnover percentage while a player is on the court	PF_TRADITIONAL: Traditional count of personal fouls committed by a player	
TM_TOV_PCT_FOUR_FACTORS: Team's turnover percentage as a part of the 'Four Factors'	TO_TRADITIONAL: Traditional count of turnovers committed by a player	
TS_PCT_ADVANCED: True shooting percentage, measuring shooting efficiency (including free throws)	PCT_PF_USAGE: Percentage of a player's personal fouls relative to their usage rate	
USG_PCT_ADVANCED: Usage percentage, indicating the proportion of team plays used by a player	PCT_PFD_USAGE: Percentage of a player's personal fouls drawn relative to their usage rate	
USG_PCT_USAGE: Similar to usage percentage, a measure of how involved a player is in team plays		

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