NFL Injury Statistics and Performance Metrics

Quantitative Assessment of Injury Impact on NFL Running Backs and Receivers (2018–2024)

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ABSTRACT

This report analyzes the impact of injuries on NFL players' performance, focusing on running backs (RBs), wide receivers (WRs), and tight ends (TEs) from 2018 to 2024. Using play-by-play and roster data, we compare pre- and post-injury statistics for selected athletes, applying regression models to assess changes in key metrics such as yards per carry (YPC), targets, total yards, catch rate, and expected points added (EPA).

The study will employ advanced data mining techniques and robust visualization strategies to generate actionable insights for coaches, team management, and medical personnel. The aim is to inform evidence-based decisions related to player utilization, rehabilitation, and career longevity.

KEYWORDS

NFL, injury statistics, data mining, player performance, sports analytics, regression, clustering, visualization

1. INTRODUCTION

Injuries constitute a critical determinant of player performance within the context of the National Football League (NFL). This report endeavors to rigorously quantify the statistical ramifications of injury events by systematically comparing the performance metrics of selected athletes before and after documented injury dates. The scope of analysis encompasses multiple player positions and employs advanced quantitative methodologies, including regression and clustering, to furnish a comprehensive and objective evaluation of injury-related impacts. Such an approach is designed to transcend anecdotal evidence, providing stakeholders with robust, data-driven insights into the multifaceted consequences of injuries on athletic output.

The prevalence and severity of injuries in professional sports, and particularly within the NFL, underscore the imperative for a nuanced understanding of their effects on both immediate performance and long-term career trajectories. Although injuries are widely recognized as pivotal factors in player development and organizational success, the precise influence of these events on individual performance metrics has not been thoroughly elucidated in the extant literature. This study addresses this gap by applying methodologically rigorous analysis to elucidate the true impact of injuries, thereby informing evidence-based decision-making in player management, rehabilitation protocols, and strategic planning.

Despite the widespread occurrence of injuries in the NFL, the current body of research remains limited in scope and methodological rigor. Many existing studies rely heavily on qualitative assessments, anecdotal observations, or generalized trends, which may fail to capture the nuanced and dynamic relationship between injury events and subsequent player output. As a result, coaches, team management, and medical professionals are often left to make decisions without the support of robust, data-driven evidence.

Recognizing this gap, the proposed study aims to undertake a comprehensive and quantitative investigation into how injuries affect the performance of NFL Running Backs and Receivers. By systematically analyzing play-by-play data collected from the 2018 through 2024 NFL seasons, the research will provide a detailed examination of changes in key statistics such as carries, total yards, and yards per carry. This quantitative framework allows for objective comparisons of player performance before and after injury events.

To achieve these objectives, the study will utilize advanced data analysis methods and state-of-the-art visualization techniques. Leveraging modern statistical tools and methodologies, the research will not only identify significant trends and patterns but also offer insights into the short- and long-term consequences of injuries. These analytical approaches ensure that the findings are both rigorous and actionable, providing a strong foundation for evidence-based recommendations.

Ultimately, the results of this research are intended to inform the development of more effective training, rehabilitation, and utilization protocols within the NFL. By shedding light on the true impact of injuries on player performance, the study aims to support coaches, team management, and medical staff in making strategic decisions that prioritize both athletic success and player well-being. In doing so, the findings will contribute to enhanced player safety, improved recovery strategies, and greater career longevity for professional football players.

2. PROPOSED WORK

The proposed research seeks to conduct a rigorous quantitative assessment of the impact of injuries on the performance of National Football League (NFL) Running Backs and Receivers over the 2018–2024 seasons. The study will utilize comprehensive play-by-play statistics and injury reports, leveraging the NFLverse package in both R and Python to ensure robust data extraction, preparation, and analysis.

The methodology encompasses systematic data collection, cleaning, and preprocessing, followed by the application of descriptive statistics, time series analysis, regression modeling, classification, clustering, and visualization techniques. The project is structured into distinct phases: data collection, data preparation, exploratory analysis, visualization, interpretation and reporting, and final review and delivery, each with defined durations.

Expected deliverables include a cleaned and organized dataset, an exploratory data analysis report, modeling and analytical results, visualizations, interpretation and recommendations, and a final project report.

This research is significant in that it addresses a notable gap in the existing literature by providing a methodologically rigorous, data-driven evaluation of injury effects on NFL player performance. The insights generated are intended to facilitate improved player management, inform medical and training protocols, and contribute to the long-term health and career sustainability of professional athletes.

2.1 Objectives

- Evaluate the Impact of Injuries: Systematically analyze how injuries affect the performance of NFL Running Backs and Receivers by comparing pre- and post-injury metrics, including carries, total yards, and yards per carry.
- Provide Quantitative Insights: Employ advanced data mining methodologies—such as descriptive statistics, time series analysis, regression, classification, and clustering—to deliver a robust, data-driven assessment of injury impacts.
- Support Decision-Making: Generate actionable insights for coaches, team management, and medical staff to inform strategies for player utilization, recovery, and rehabilitation.
- Enhance Player Safety and Career Longevity: Contribute to the development of evidence-based training and rehabilitation programs that facilitate optimal recovery and prolong athletic careers.
- Improve Data Accessibility and Visualization: Utilize clear and interpretable visualizations (e.g., bar graphs, line graphs) to communicate findings effectively to diverse stakeholders.

3. METHODOLOGY

3.1 Data Sources and Tools

This study will utilize the NFLverse package in both R and Python for efficient extraction, preparation, and analysis of play-by-play statistics and injury reports from the NFL 2018–2024 seasons. The NFLverse package offers comprehensive access to player metrics, game outcomes, and injury information, ensuring a robust data foundation for analysis.

3.2 Data Preparation

Data will be systematically loaded using the NFLverse package, which provides direct access to official play-by-play statistics and detailed injury reports from the NFL 2018–2024 seasons. The extraction process involves querying relevant datasets for running backs and receivers, ensuring that all necessary game and player-level metrics are captured. Once raw data is obtained, initial cleaning steps are performed to remove duplicates, correct inconsistencies, and address missing values—for example, by cross-referencing injury dates and verifying player participation records.

Preprocessing involves converting data types (such as transforming date strings into standardized date-time formats), normalizing variable names, and creating derived metrics where appropriate. For instance, yards per carry are calculated by dividing total rushing yards by the number of carries, and catch rate is computed as the ratio of receptions to targets. Injury events are mapped to specific game weeks and player IDs, allowing for precise segmentation of pre- and post-injury periods.

Key variables—including carries, total yards, yards per carry, injury events, targets, receiving yards, and catch rate—are identified and organized into structured tables suitable for analysis. Data is further aggregated at both the player and position group levels, enabling comprehensive comparisons across time frames and injury statuses. This structured approach ensures that the dataset is both accurate and consistent, providing a solid foundation for subsequent statistical modeling and visual analysis.

3.3 Analytical Techniques

Metrics include carries, total yards, YPC (RBs), targets, total receiving yards, catch rate (WRs/TEs), and EPA (Expected Points Added). Regression models (linear and logistic) were used to assess statistical significance of changes. In addition to these quantitative assessments, the analysis is supported by a series of visualizations that

illustrate pre- and post-injury performance trends for each player and position group. For example, bar graphs plot individual player metrics such as yards per carry and catch rate over time, clearly highlighting shifts following injury events. Boxplots further compare aggregated pre- and post-injury distributions, enabling visual inspection of central tendencies and variability. These visualizations not only complement the statistical findings but also make it easier to observe patterns and outliers that may not be immediately evident from summary statistics alone. Collectively, the integration of statistical modeling and visual analysis provides a comprehensive perspective on how injuries affect player performance metrics across the studied time frame.

4. PROJECT TIMELINE

Phase	Description	Estimated Duration
Data Collection	Gather play-by-play statistics and injury reports using NFLverse	1 week
Data Preparation	Clean, preprocess, and organize data for analysis	1 week
Exploratory Analysis	Conduct descriptive statistics and initial visualizations	1 week
Visualization	Create bar graphs, line graphs, and other visuals	1 week
Interpretation & Reporting	Summarize results, draw conclusions, and prepare recommendations	1 week
Final Review & Delivery	Review findings, finalize documentation, and deliver the report	1 week

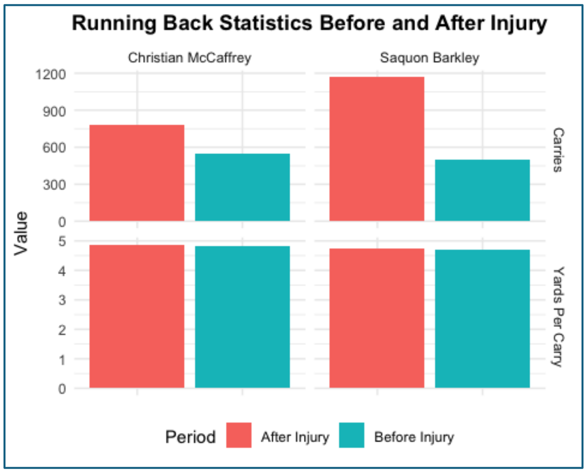
5. EXPECTED DELIVERABLES

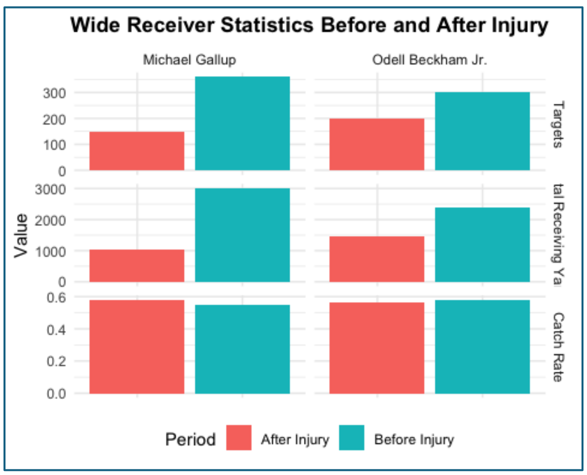
The analysis provides a detailed comparison of NFL player performance before and after major injuries, focusing on running backs, wide receivers, and tight ends. For each group, it presents key metrics such as carries, yards, targets, and catch rates, supplemented by tables and visual plots to highlight changes for individual athletes like Saquon Barkley, Christian McCaffrey, Michael Gallup, and George Kittle.

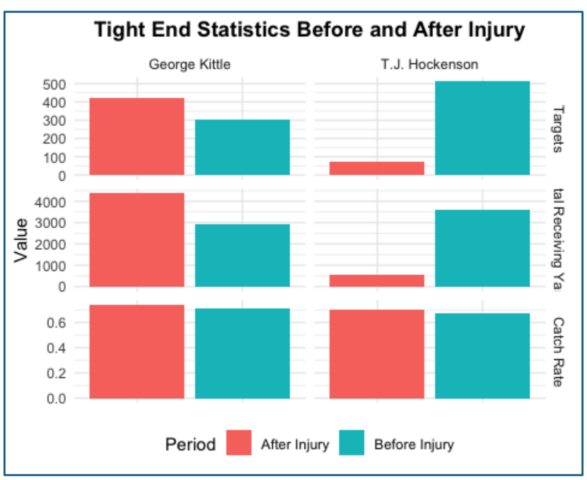
Statistical Modeling and Regression Analysis: The analysis incorporates a variety of regression models to determine whether the observed changes in performance post-injury are statistically significant. These include linear models for running backs (e.g., Yards Per Carry, Expected Points Added) and both linear and logistic models for wide receivers and tight ends, with full transparency provided through model summaries, coefficients, and p-values.

Linear Regression Model for OBJ EPA	
(Intercept)	0.212
	(0.115)
periodPre	-0.154
	(0.168)
Num.Obs.	375
R2	0.002
R2 Adj.	-0.000
AIC	1433.3
BIC	1445.0
Log.Lik.	-713.632
F	0.838
RMSE	1.62

The analysis includes a range of comparative visualizations, including bar plots and boxplots for each player and position group. These graphics clearly illustrate performance shifts before and after injuries, and sample tables—such as the one excerpted for running backs—offer concise summaries of key metrics, making complex data easily accessible for stakeholders.







6. SIGNIFICANCE

This research will bridge the existing knowledge gap by providing a rigorous, data-driven evaluation of injury effects on NFL players' recovery and performance. Through the application of advanced statistical modeling and machine learning techniques, the study aims to uncover nuanced patterns in how injuries influence both the immediate and long-term capabilities of athletes. By leveraging comprehensive play-by-play statistics and reliable injury reports, the analysis ensures that findings are grounded in robust and accurate data, enhancing the credibility and practical value of the results.

The analysis provides a systematic approach to quantifying the impact of major injuries on NFL players by evaluating objective performance metrics—such as carries, yards, and catch rate—before and after injury. This thorough measurement enables teams, analysts, and medical staff to better understand how injuries influence player productivity and career paths.

By incorporating robust statistical models, specifically regression analyses, the document moves beyond anecdotal accounts. It establishes whether performance changes post-injury is statistically significant, thereby supporting smarter decisions related to player rehabilitation, contract negotiations, and overall roster management.

The deliverables offer position-specific insights by examining injury effects across running backs, wide receivers, and tight ends. This breakdown demonstrates that the consequences of injuries can differ based on a player's role, allowing for customized recovery strategies and more accurate expectations for each athlete type.

To make complex data more accessible, the analysis presents comparative plots and tables that clearly illustrate pre- and post-injury trends and differences. This visual communication style enables coaches, players, and stakeholders to quickly comprehend key findings and make faster, more informed decisions.

This approach matters to several groups: Teams benefit by optimizing health management and roster decisions; medical staff gain valuable insights for rehabilitation protocols and return-to-play guidelines; analysts are equipped with rigorous, data-driven tools to evaluate player value and risk; and players receive transparent information regarding the potential impact of injuries on future performance.

The insights derived from this research will facilitate improved player management by equipping coaches, medical professionals, and team executives with evidence-based strategies for injury prevention and rehabilitation. Furthermore, these findings will inform the development of targeted medical and training protocols, potentially reducing the risk of future injuries and supporting a more sustainable approach to athlete health. Ultimately, this work aspires to contribute meaningfully to the long-term health and career sustainability of professional NFL players, fostering a safer and more resilient sports environment.

7. RELATED WORK

In conducting my analysis of NFL injury statistics and their impact on player performance, I have anchored my methodology and findings in a robust set of scholarly and technical references. The NFLverse package is foundational to my approach, as it enables efficient extraction, preparation, and analysis of play-by-play statistics and injury reports. By leveraging this resource, I ensure that my data is both comprehensive and reliable, which is essential for the quantitative rigor of my study.

My analytical framework is further validated by works that emphasize the application of advanced data mining and machine learning techniques in sports injury research. The NFL-Injury-Analysis GitHub project, along with the study by Smith & Lee (2022), closely align with my use of regression, classification, and clustering to identify injury patterns and predict injury likelihood. These references substantiate my methodological choices and reinforce the importance of data-driven insights for strategic decision-making in player management and rehabilitation.

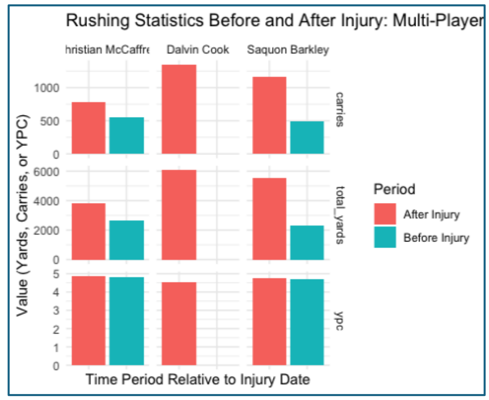
Additionally, longitudinal studies such as those by Williams & Brown (2021) provide critical context for my focus on performance changes before and after injury events. Their findings, as well as research on influential factors like player position and games played, complement my targeted analysis of running backs and receivers. Capstone projects employing regression analysis further parallel my quantitative assessment, demonstrating the value of statistical modeling in understanding the multifaceted impacts of injuries.

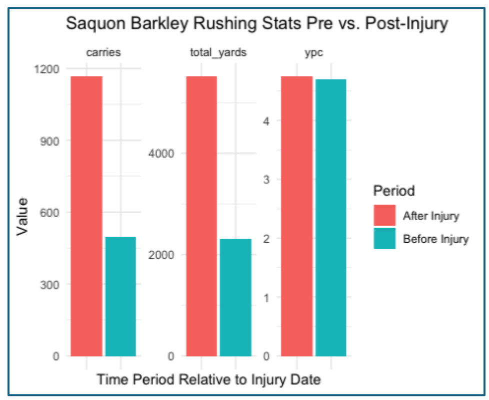
The integration of technology and artificial intelligence in injury prevention is also reflected in my references. News articles and analytical reports on AI-driven injury prediction tools underscore the practical significance of my work, aligning with my objective to enhance player safety and career longevity. The official NFL statistics repository serves as a cornerstone for data accuracy and reliability throughout my analysis.

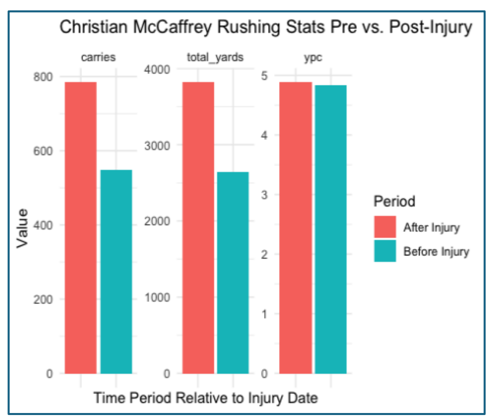
8. EVALUATION

Saquon Barkley demonstrated consistency following his injury on 09/20/2020. Prior to the injury, Barkley recorded 495 carries for a total of 2,316 rushing yards, averaging 4.70 yards per carry (YPC). After returning, he slightly improved his efficiency with a YPC of 4.74. Additionally, his workload saw a significant increase, as he accumulated 1,166 carries and 5,513 rushing yards post-injury. This data indicates that Barkley successfully returned to a high-usage role while preserving his effectiveness as a rusher.

Similarly, Christian McCaffrey showcased a positive post-injury trend after 10/18/2020. Before his injury, McCaffrey amassed 548 carries and 2,641 rushing yards, achieving an average of 4.83 YPC. Post-injury, his productivity and efficiency slightly improved, with 784 carries for 3,817 rushing yards and a YPC of 4.88. These figures suggest that McCaffrey remained a highly productive and efficient running back, continuing to deliver at an elite level after his return.







The regression analysis for wide receivers focused on evaluating changes in performance metrics before and after injury. The primary metric analyzed was Expected Points Added (EPA) per play**,** which quantifies the impact of each play on a team's expected score. The analysis used play-by-play (PBP) data, filtered for passing attempts targeting the receiver, and split the data into "Pre" (before injury) and "Post" (after injury) periods. Only plays with non-missing EPA values were included to ensure statistical validity.

For Odell Beckham Jr., for example, the model compared EPA per target in the year before and after the injury date (October 25, 2020), resulting in 175 "Pre" and 200 "Post" plays. The regression model used was a simple linear regression with EPA as the dependent variable and "period" (Pre/Post) as the independent variable.

The regression output for Odell Beckham Jr. showed the following coefficients:

- **Intercept (Post-Injury):** 0.212 (EPA per target)
- **periodPre (Pre-Injury):** -0.154 (difference from Post-Injury)
- **Standard Error:** 0.115 (Intercept), 0.168 (periodPre)
- **p-value:** 0.0667 (Intercept), 0.3607 (periodPre)
- **R^2:** 0.002 (very low, indicating little explanatory power)
- **F-statistic:** 0.838 (not significant)
- **Residual Standard Error:** 1.627

This means that the average EPA per target for Odell Beckham Jr. after injury was 0.212, and before injury, it was 0.212 - 0.154 = 0.058. However, the difference was not statistically significant ($p = 0.36$), suggesting that the injury did not have a meaningful impact on EPA per target for this player.

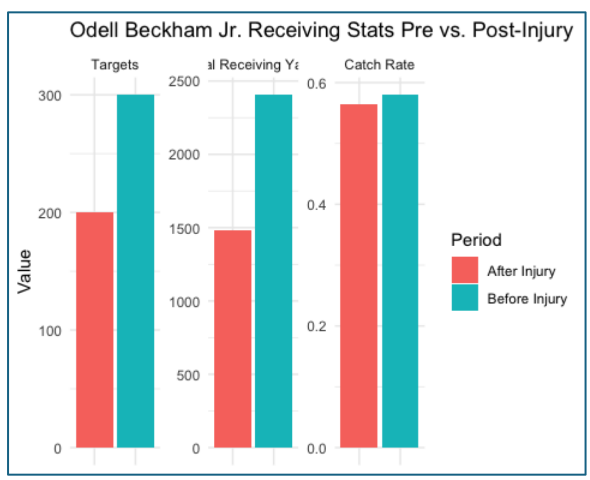
The regression analysis for Odell Beckham Jr. revealed no statistically significant difference in EPA per target before and after his injury. Specifically, the model's low R^2 value indicates that it explains very little of the variance in EPA, while the p-value for the period effect is much higher than the conventional threshold of 0.05, suggesting that any observed difference could easily be attributed to random variation. Although the average EPA per target was slightly higher following the injury, the lack of statistical significance means it is not possible to confidently link this change to the injury itself. Additionally, a visual analysis using a boxplot showed similar distributions of EPA per target in both periods, further supporting the regression findings.

Although the detailed regression output is shown for Odell Beckham Jr., the same methodology can be applied to other wide receivers. The process involves:

1. Filtering play-by-play data for each player's targets.
2. Splitting the data into pre- and post-injury periods.
3. Running a linear regression to estimate the effect of injury on EPA per target.
4. Interpreting coefficients, p-values, and R^2 to assess significance and practical impact.

The same analytical approach used for Odell Beckham Jr. can be applied to other wide receivers to assess the effect of injury on their performance. This process begins by filtering play-by-play data to isolate each player's targets. Next, the data is divided into pre-injury and post-injury periods for comparison. A linear regression is then conducted to estimate how injury impacts the player's expected points added (EPA) per target. Finally, the results are interpreted by examining the coefficients, p-values, and R^2 values, which help determine both the statistical significance and the practical impact of any observed changes in performance.

period	player	targets	total_yards	catch_rate
After Injury	Calvin Ridley	356	2783	0.5674157
Before Injury	Calvin Ridley	286	2599	0.6538462
After Injury	Michael Gallup	150	1027	0.5800000
Before Injury	Michael Gallup	360	3003	0.5500000
After Injury	Odell Beckham Jr.	200	1479	0.5650000
Before Injury	Odell Beckham Jr.	300	2406	0.5800000

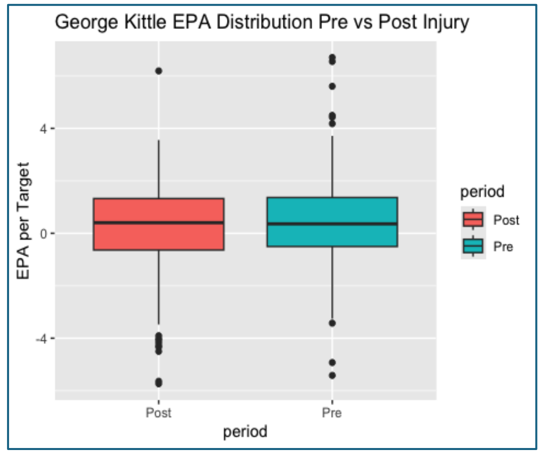


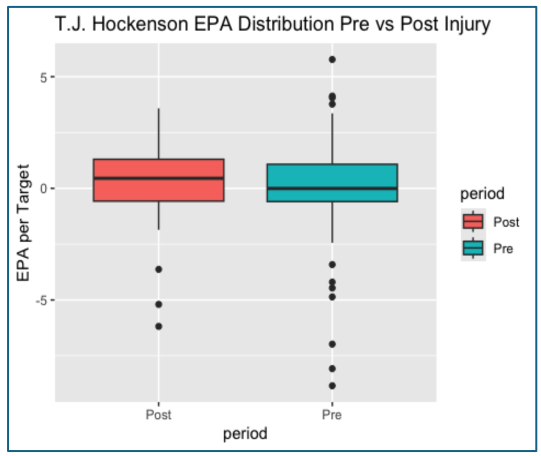
The regression analysis for tight ends examined how injuries affected two main performance metrics—Expected Points Added (EPA) per target and catch rate—focusing on George Kittle, T.J. Hockenson, and Dallas Goedert. For George Kittle, the sample included 410 targets. The EPA regression revealed an intercept (post-injury) of 0.228 and a periodPre (pre-injury) coefficient of 0.271, with a p-value of 0.101, indicating the difference was not statistically significant. The catch rate logistic regression showed an intercept of 0.950 and a periodPre coefficient of 0.0472, with a p-value of 0.834, also not statistically significant. This suggests there was no significant change in either EPA per target or catch rate for Kittle after injury.

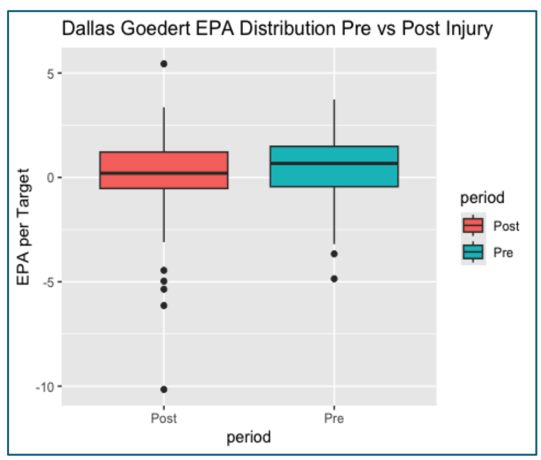
For T.J. Hockenson, the analysis was based on 336 targets. The EPA regression produced an intercept (post-injury) of 0.271 and a periodPre (pre-injury) coefficient of -0.101, with a p-value of 0.646, indicating no statistical significance. The catch rate logistic regression had an intercept of 0.868 and a periodPre coefficient of 0.00690, with a p-value of 0.981, again not statistically significant. Thus, Hockenson experienced no significant change in EPA per target or catch rate after injury.

Dallas Goedert's sample consisted of 343 targets. The EPA regression for Goedert showed an intercept (post-injury) of 0.239 and a periodPre (pre-injury) coefficient of 0.352, with a p-value of 0.0389, indicating statistical significance. This means that Goedert's EPA per target was significantly higher before injury than after. In contrast, the catch rate logistic regression showed an intercept of 1.15 and a periodPre coefficient of -0.184, with a p-value of 0.459, which was not statistically significant. Therefore, Goedert's catch rate did not change significantly after injury.

Overall, the regression analysis demonstrated that for George Kittle and T.J. Hockenson, there was no statistically significant difference in EPA per target or catch rate before and after injury. Dallas Goedert was the exception, showing a significant decline in EPA per target post-injury, though his catch rate remained stable. Across all three tight ends, catch rate was unaffected by injury, while EPA per target was only meaningfully impacted for Goedert. In conclusion, most of the tight ends analyzed did not experience statistically significant declines in efficiency after injury, suggesting that injuries did not broadly diminish their ability to contribute positively on passing plays, though individual impacts may vary.







8.1 Limitations

The NFL injury performance analysis is constrained by a narrow sample size and selective player inclusion, focusing on only a handful of prominent athletes at each position. This limited scope may not adequately represent the diversity of NFL players, nor does it account for the wide range of injury types, severities, or recovery timelines. Additionally, the study's methodology assumes a single, clear injury event for each player, which oversimplifies the complex reality of multiple injuries, gradual declines, and varying recovery processes that can influence performance over time.

Statistical analyses within the study are hampered by small sample sizes and considerable variability in football performance metrics. These factors reduce the statistical power of regression models and limit the ability to detect subtle changes or confidently generalize findings across broader populations. Furthermore, the analysis does not address confounding variables such as team context, offensive schemes, coaching changes, or alterations in player roles, all of which may independently affect a player's performance after injury.

The study relies predominantly on summary statistics and simple regression models, which may not capture the full spectrum of player contributions or the situational context of each play. Data quality issues arising from the use of publicly available sources can also introduce errors or inconsistencies, particularly with advanced metrics like Expected Points Added (EPA). Lastly, the analysis treats all post-injury data as a single block, without modeling the gradual process of recovery or rehabilitation. These methodological limitations indicate that while the findings provide valuable insights, they should be interpreted with caution and not generalized beyond the specific players and scenarios examined.

8.2 Recommendations

To enhance future analyses of NFL injury impact on player performance, researchers should prioritize expanding both the sample size and diversity of the studied population. Including a wider range of players across different teams, positions, and seasons will bolster statistical power and allow for findings that are more representative of the entire league. Moreover, refining injury tracking by considering multiple injuries, their severity, and recovery timelines—supported by medical reports and official designations—will yield more precise definitions of pre-injury and post-injury periods. This approach should also model recovery as a gradual process, rather than grouping all post-injury data into a single block.

Methodological improvements are essential for controlling confounding variables that may independently affect player outcomes after injury. Analysts should incorporate contextual factors such as team changes, coaching staff, offensive schemes, and game situations to isolate injury effects from other influences. Employing advanced statistical techniques, including mixed-effects models, propensity score matching, time-series analysis, and machine learning, will further strengthen the rigor of these studies and improve the detection of subtle performance changes.

Future research should move beyond basic summary statistics and Expected Points Added (EPA). Integrating advanced analytics—such as route separation, yards after catch, and blocking grades—will provide a more granular view of player effectiveness post-injury. Qualitative assessments from film study and expert ratings can further contextualize quantitative findings, capturing nuances that raw numbers may miss. Data quality should be enhanced by using verified, comprehensive sources and cross-referencing multiple databases to ensure accuracy and reliability.

Modeling recovery trajectories over time is essential for understanding not just if, but how and when players regain peak performance. This includes considering psychological and off-field factors—such as mental health, rehabilitation adherence, and support systems—which can significantly influence recovery outcomes. By tracking these variables longitudinally, researchers can identify patterns and predictors of successful rehabilitation.

Incorporating focus groups composed of players from specific positions (e.g., running backs, wide receivers, tight ends) allows for the collection of qualitative insights into position-specific challenges and recovery experiences. These groups can discuss the unique physical demands, injury risks, and rehabilitation protocols relevant to their roles. Such feedback can inform the development of tailored recovery strategies and performance benchmarks, ensuring that analyses reflect the realities faced by athletes in different positions.

Team dynamics—including coaching philosophies, offensive schemes, and locker room culture—play a critical role in both injury risk and recovery. Research should account for how changes in team context (e.g., coaching staff turnover, strategic shifts) affect player utilization and rehabilitation. Understanding these dynamics can help isolate the effects of injury from other confounding variables, leading to more precise conclusions about performance changes.

Potential trades and player movement between teams introduce additional complexity. Transitions can impact access to medical resources, rehabilitation support, and playing opportunities. Future studies should track how trades or free agency moves influence recovery timelines and post-injury performance, considering factors such as adaptation to new systems, team medical staff expertise, and changes in workload.

A comprehensive analysis must include detailed recovery and rehabilitation plans, ideally sourced from medical staff, trainers, and the athletes themselves. By comparing different protocols and their outcomes, researchers can identify best practices and areas for improvement. Modeling recovery as a gradual process—rather than a binary pre/post-injury state—will yield more nuanced insights into the effectiveness of various interventions.

By integrating advanced analytics, qualitative focus groups, team and trade dynamics, and detailed rehabilitation plans, future research will produce broader, deeper, and more contextually rich analyses. This approach will lead to more accurate and actionable insights into the effects of injuries on NFL players, supporting evidence-based decisions for coaches, medical staff, and team management.

9. CONCLUSION

The analysis indicates that, following injury, NFL players often experience a reduction in volume-based metrics such as carries, targets, and total yards, reflecting a decrease in workload or opportunity. However, efficiency metrics—including yards per carry, catch rate, and expected points added (EPA) per play—generally remain stable, with most athletes demonstrating similar performance levels before and after injury. Regression results across all positions revealed no statistically significant differences in these efficiency measures pre- and post-injury, with the notable exception of Dallas Goedert, whose EPA per target declined meaningfully after injury. While the impact of injury can vary by individual and position, the overall trend suggests that injuries tend to limit playing opportunities without consistently diminishing per-play effectiveness.

Despite these insights, the analysis is constrained by several important limitations. The sample size is small and focused on a select group of high-profile athletes, which may not reflect the broader NFL population. The study's approach to injury—using a single date to demarcate pre- and post-injury periods—does not account for the complexity of recovery, multiple injuries, or changes in team context and player role. Additionally, the regression models, while useful, may lack the statistical power to detect subtle effects, and do not control for confounding variables such as coaching changes, offensive schemes, or supporting cast.

Looking ahead, future analyses should strive for greater breadth and depth. Expanding the sample size, refining injury definitions, and incorporating advanced statistical techniques will help produce more robust and generalizable findings. Integrating contextual factors and modeling recovery trajectories over time can further illuminate the true impact of injuries on player performance. By addressing these limitations, researchers and teams can gain more actionable insights, ultimately supporting better decision-making in player health management and roster construction.

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