NFL RB Workload and Efficiency

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1. Abstract

The performance of NFL running backs (RBs) has long been a focus of interest among coaches, analysts and fans, particularly concerning the relationship between workload and efficiency. Workload, typically measured as total touches (carries plus receptions), directly influences a player's production, durability, and career longevity. While conventional wisdom suggests that heavier workloads may reduce per-touch efficiency due to fatigue, many NFL teams have historically relied on a "workhorse" RB who receives a large share of touches over the course of a season. This study investigates how running back workload affects efficiency, measured in yards per touch, using nearly three decades of NFL data from 1996 to 2024.

The motivation for this project is both practical and theoretical. NFL teams invest heavily in running backs, and understanding the efficiency implications of high workloads can inform player management and roster strategy. From a research perspective, this study addresses the statistical modeling of player performance by combining exploratory data analysis, hypothesis testing, regression modeling, and clustering to provide a comprehensive view of workload effects. The initial hypothesis posits that higher workloads correspond to modest reductions in per-touch efficiency, with extreme workloads (>300 touches) potentially intensifying this effect.

Prior studies have examined the relationship between player usage and performance in professional football. For instance, Sanchez et al. (2023) quantified position-specific physical demands in the NFL, highlighting that running backs experience high-intensity workloads that can influence per-game performance. Similarly, Yurko, Ventura, and Horowitz (2018) developed reproducible metrics for evaluating offensive player efficiency, emphasizing the importance of both volume and situational context in assessing performance outcomes. Building on these insights, this study leverages publicly available game-level statistics from Pro-Football-Reference to quantify workload-efficiency relationships and identify natural groupings of RB performance profiles.

Ultimately, this study aims to provide both analytical rigor and practical insights, contributing to a deeper understanding of how workload management influences RB productivity in modern NFL offenses.

2. Data Description and Preliminary Analysis

This section introduces the primary dataset of NFL running back (RB) scrimmage statistics and presents an initial examination of workload and efficiency metrics. The goal is to provide a foundational understanding of the data, including its structure, variables, and coverage across seasons. Key preprocessing steps, such as filtering for RBs and excluding seasons with fewer than 50 total touches, are also described, along with a preliminary exploration of summary statistics and visualizations to highlight typical performance patterns. These analyses set the stage for the more detailed exploratory analysis in Section 3.

2.1 Data Description

For this project, the primary dataset consists of NFL running back (RB) scrimmage statistics spanning from the 1996 to 2024 seasons. The data was obtained from Pro-Football-Reference, a widely used and reliable source for professional football statistics. Pro-Football-Reference provides detailed season statistics for individual players, including rushing, receiving, and combined scrimmage metrics. This dataset was selected because it provides comprehensive coverage of all NFL teams and RBs across the past 25+ years, ensuring a broad and representative sample.

To collect the data, web scraping was performed using R and the rvest package. A script iterated over the years 1996 through 2024, constructing a URL for each season's scrimmage statistics page. For each page, the HTML table containing scrimmage data was extracted and saved as a CSV file in a dedicated data folder. This approach allowed for the automated collection of nearly three decades of data, ensuring consistency and completeness across seasons.

Each CSV file contained two header rows. The first row represents category headers, such as “Receiving” or “Rushing,” while the second row contains the specific variable names, such as “Yds” or “TD.” During data processing, these two rows were combined into descriptive column names like Receiving_Yds and Rushing_Att, which greatly simplified later analysis. The dataset includes player identifiers (name, age, team, season), receiving and rushing statistics (yards, touchdowns, averages), scrimmage totals (touches, total yards, touchdowns), ball security measures (fumbles), and season/rank information. This combination of variables will allow the evaluation of RB efficiency relative to workload, while maintaining the context of seasonal performance.

For the purpose of this project, only rows where Pos = "RB" and total touches were at least 50 were retained. Key numeric columns, including games played, total yards, and touchdowns, were converted from character to numeric types to enable proper filtering and calculations. Derived metrics, such as touches_per_game and yards_per_game, were computed to standardize performance across RBs with differing workloads. Additionally, the original seasonal rank was preserved as season_rank, while a new total_yds_rank was calculated to compare RBs across all seasons based on total scrimmage yards.

The final dataset contains 38 variables statistics, with each row representing a single RB in a single NFL season. Its structure allows for both cross-sectional analysis within a given season and longitudinal comparisons across multiple seasons. This structured, comprehensive dataset provides a solid foundation for analyzing the relationship between running back workload and efficiency over nearly three decades of NFL play.

2.2 Preliminary Analysis

With the dataset cleaned and processed, we first examine key summary statistics to understand typical RB workloads and efficiency metrics.

Figure 1: Summary of RB Workload and Efficiency Metrics

```
Scrimmage_Touch Scrimmage_YScm   Scrimmage_Y.Tch touches_per_game yards_per_game
Min.   : 50.0   Min.   : 138.0   Min.   : 2.30   Min.   : 3.00    Min.   :  8.118
1st Qu.: 90.0   1st Qu.: 432.0   1st Qu.: 4.20   1st Qu.: 7.50    1st Qu.: 36.111
Median :152.0   Median : 723.0   Median : 4.70   Median :12.06    Median : 55.733
Mean   :174.2   Mean   : 830.1   Mean   : 4.79   Mean   :12.81    Mean   : 60.700
3rd Qu.:245.0   3rd Qu.:1145.0   3rd Qu.: 5.30   3rd Qu.:17.71    3rd Qu.: 81.733
Max.   :457.0   Max.   :2509.0   Max.   :10.40   Max.   :29.62    Max.   :163.357
```

The summary in Figure 1 shows that most RBs accumulate between ~90–250 touches per season, with median efficiency around 4.7 yards per touch and ~56 yards per game. Total yards vary more widely, reflecting differences in workload and team offensive schemes.

Next, we examine histograms to visualize the distribution of key variables, including workload and efficiency.

Figure 2: Distribution of Total Touches Among RBs

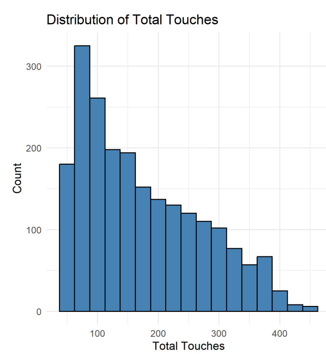


Figure 3: Distribution of Yards per Touch

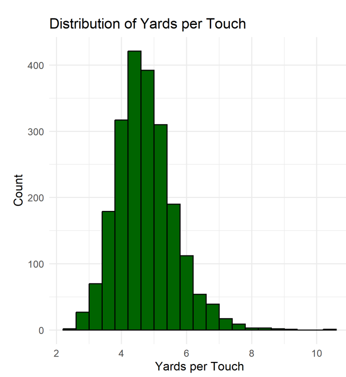
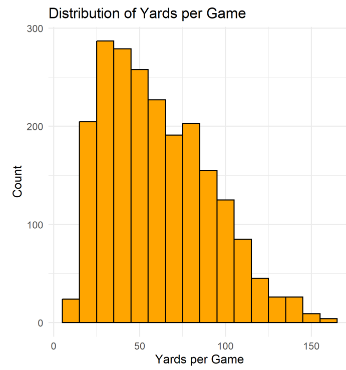


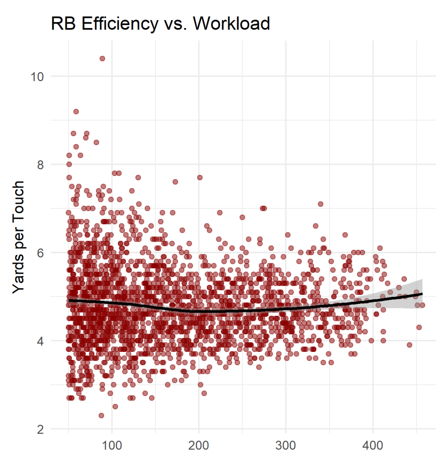
Figure 4: Distribution of Yards per Game



The histograms show that most running backs fall below 250 total touches per season, with a steep drop-off beyond 300, indicating that true 'bell cow' backs are rare. Efficiency, measured in yards per touch, is tightly clustered between 4 and 5 yards, with few players exceeding 6. Meanwhile, yards per game exhibit broader variation, reflecting the combined influence of both volume and efficiency, with some players achieving high yardage through consistent workload, while others rely on explosive playmaking.

Now, to examine potential relationships between workload and efficiency, scatter plots and boxplots were generated.

Figure 5: RB Efficiency vs. Total Touches



The scatter plot in Figure 5 suggests efficiency (yards per touch) remains relatively stable across varying workloads, with a slight upward trend suggesting that high-volume running backs can maintain or even improve their productivity.

Figure 6: Total Yards vs. Total Touches

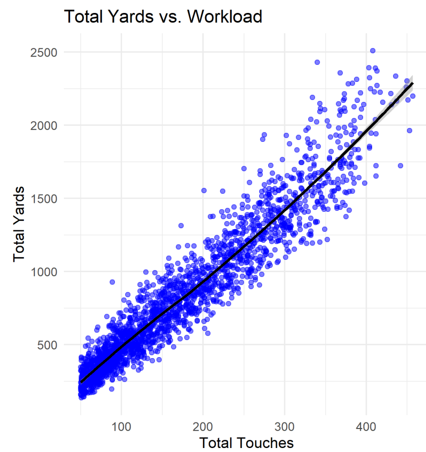


Figure 6 shows that total yardage increases with workload, as shown by the upward trend line. Running backs with more touches tend to accumulate more yards, though the rate of increase may vary across players and usage contexts.

Finally, to quantify relationships between workload and performance, simple correlation coefficients were computed:

Total Touches vs. Yards per Touch: −0.049

Total Touches vs. Yards per Game: 0.86

The weak negative correlation between total touches and yards per touch suggests that heavier workloads are slightly associated with reduced per-touch efficiency. In contrast, the strong positive correlation with yards per game indicates that total production scales with workload, indicating backs who touch the ball more frequently tend to accumulate significantly more yardage overall.

The preliminary exploration of the RB dataset reveals that most running backs operate under moderate workloads, with efficiency largely stable across a typical range of touches. While extremely high-volume backs are rare, total yardage scales predictably with touches. The correlation analysis supports the hypothesis that higher workloads may slightly reduce per-touch efficiency, though overall production increases. These insights provide a foundation for deeper exploratory analyses, including workload grouping, trend comparisons across seasons, and potential predictive modeling of efficiency metrics.

3. Exploratory Analysis

This section builds on the preliminary analysis to explore the statistical aspects of running back workload and efficiency more deeply. The goal is to investigate trends across seasons, compare performance among different workload groups, and identify potential outliers. All data preprocessing and filtering described in Section 2 was retained. Thus, only players designated as RBs were included, and seasons with fewer than 50 total touches were excluded. Key numeric columns were converted to numeric, and derived metrics such as touches per game and yards per game were used to standardize performance across players.

3.1 Workload Group Comparisons

To investigate whether efficiency varies with workload, two grouping methods were applied. First, RBs were split relative to the median total touches (152) for the dataset, resulting in "Above Median" and "Below Median" groups. Second, a fixed threshold of 300 touches was used to categorize RBs as "High" or "Low" workload. These approaches allow comparisons between workloads as well as identification of "bell cow" RBs with 300+ touches.

Figure 7: Efficiency by Workload Group (Median Threshold)

Figure 7 compares yards per touch for RBs with above- and below-median total touches. RBs with higher workloads exhibit slightly lower median efficiency, indicating that increased total touches may modestly reduce per-touch productivity.

Figure 8: Efficiency by Workload Group (300 Touches Threshold)

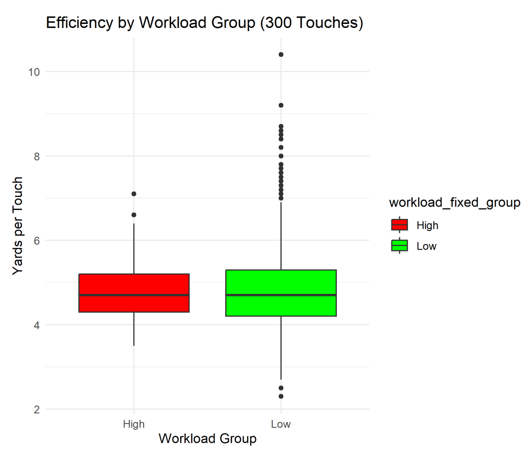


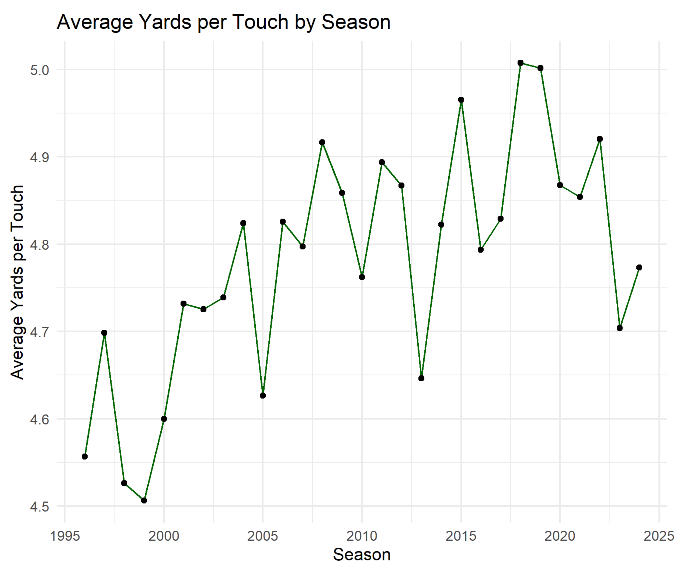
Figure 8 compares yards per touch for RBs with more than 300 touches versus those with fewer. The figure highlights that extremely high workloads have a median nearly identical to RBs with less than 300 touches. It also shows that most RBs in this higher workload group maintain a more consistent per-touch performance, as the range of values is less spread.

The boxplots show that while efficiency may decrease slightly for heavier workloads, distributions are fairly tight, suggesting that RBs generally maintain their productivity regardless of moderate variations in touches. A small number of extreme performers fall outside the interquartile range, representing unusually efficient or heavily utilized seasons.

3.2 Seasonal Trends

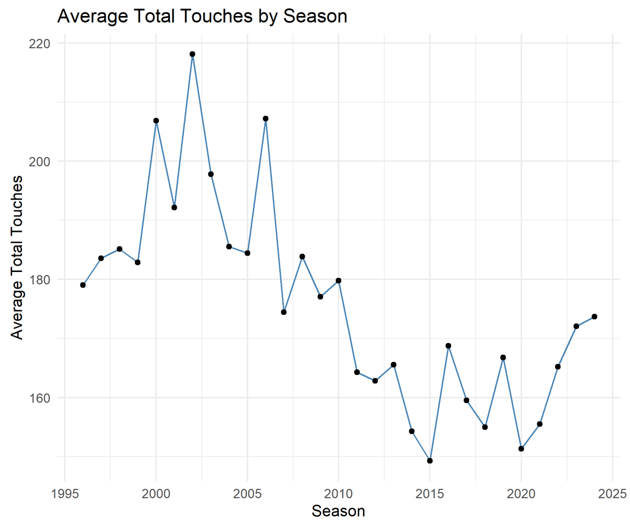
To explore longitudinal patterns, seasonal averages were calculated for total touches, yards per touch, and yards per game.

Figure 9: Average Yards per Touch by Season



Line plot showing the mean yards per touch for all RBs in each season from 1996 to 2024. Efficiency remains relatively stable over time within the range 4.5-5.0 yards per touch, though slight seasonal fluctuations may correspond to changes in offensive strategies or the emergence of particularly dominant players.

Figure 10: Average Total Touches by Season



Line plot illustrating the mean total touches per RB per season. Trends suggest a gradual decrease in RB usage, with occasional spikes corresponding to seasons featuring high-volume workhorse backs.

These plots reveal that while RB efficiency is relatively consistent across decades, total workload has generally decreased gradually over time. There are occasional spikes in workload averages, likely due to team usage patterns and differing offensive schemes. Overall, it does seem that the recent emergence of multi-back rotations has contributed to a decrease in player touches on averages. It's also important to note that seasons of 2015 and 2020 appear to be among the lowest in workload averages, and among the highest in efficiency.

3.3 Distributional Analysis

Next, the distributions of efficiency and workload between the separated Workload groups were examined to identify patterns, skewness, and outliers.

Figure 11: Density of Yards per Touch by Median Workload Group

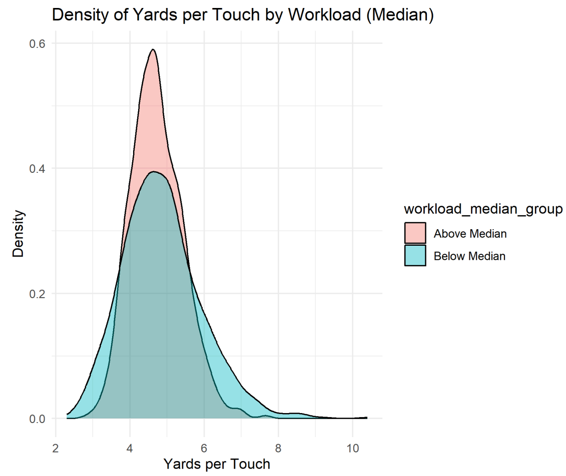
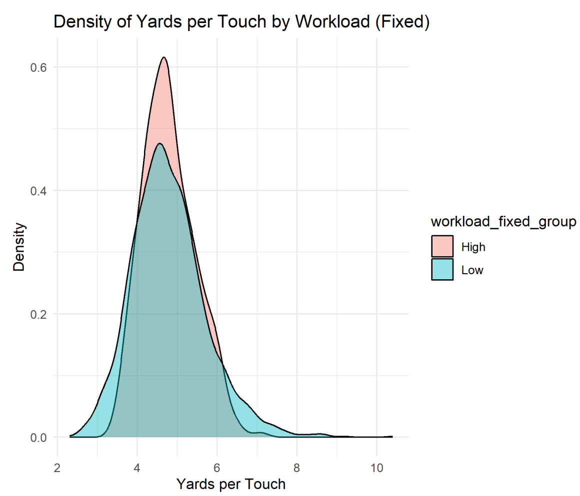


Figure 12: Density of Yards per Touch by Fixed Workload Group



Figures 11 and 12 compare the distribution of yards per touch for RBs across both the Median Workload Group and the Fixed (> 300 Touch) Workload Group. Efficiency is tightly clustered around 4–5 yards per touch, with a few extreme performers exceeding 6 yards per touch.

Figure 13: Distribution of Total Touches by Median Workload Group

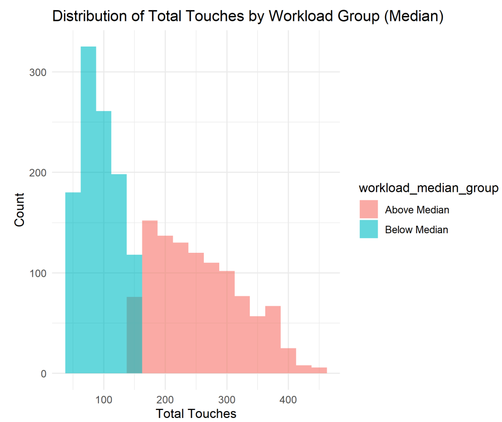
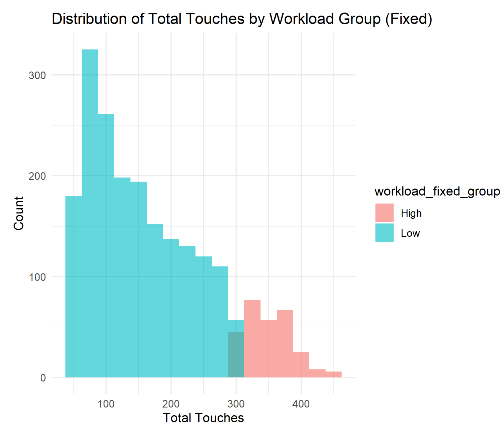


Figure 14: Distribution of Total Touches by Fixed Workload Group



Figures 13 and 14 are histograms showing total touches for RBs across both the Median Workload Group and the Fixed (> 300 Touch) Workload Group. The distributions depict the large counts of RBs that fall between 50-150 total touches. The distribution also has a skewed right tail, reflecting the rarity of extremely high-volume RBs.

These figures highlight the relative consistency of RB efficiency across both groups in both workloads, though RBs in the higher workload groups seem to have a more tight spread, with most values between 3.8 and 6. The histograms distributions also show the skewed nature of workload, emphasizing the small proportion of RBs with exceptionally high touches.

3.4 Correlations and Pairwise Exploration

To quantify relationships among workload and performance metrics, pairwise correlations were computed. To reiterate:

Total Touches vs. Yards per Touch: −0.049

Total Touches vs. Yards per Game: 0.86

These values indicate that while running backs with higher workloads tend to maintain similar per-touch efficiency, there is a slight decrease in yards per touch as touches increase. In contrast, total production, both in terms of yards per game and total scrimmage yards, increases substantially with workload.

Figure 13: Correlation Matrix of Key Performance Metrics

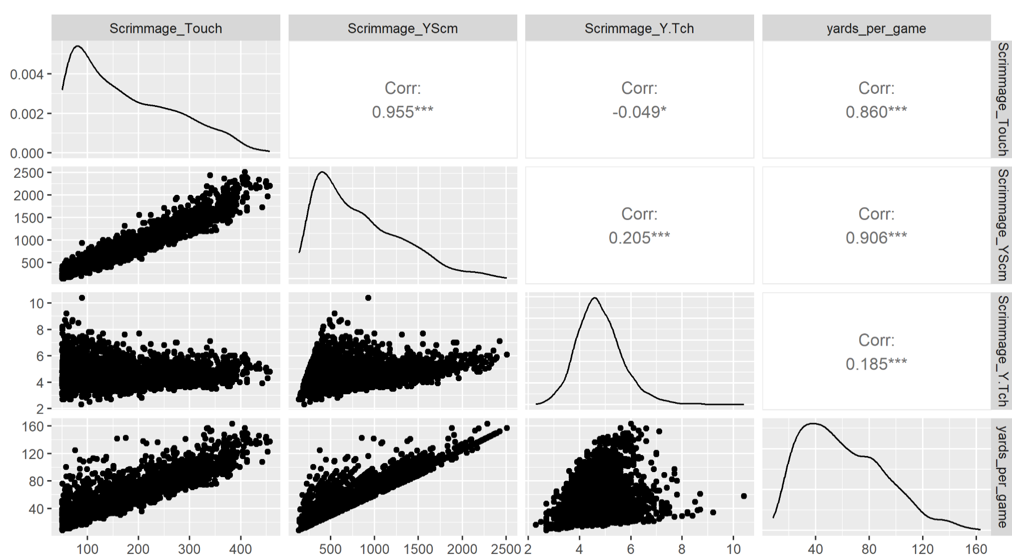


Figure 13 depicts a heatmap displaying the Pearson correlation coefficients among total touches (Scrimmage_Touch), total scrimmage yards (Scrimmage_YScm), yards per game (yards_per_game), and yards per touch (Scrimmage_Y.Tch). Darker shades indicate stronger positive correlations, while lighter or reddish shades indicate negative correlations. This visualization confirms the quantitative results: heavier workloads are slightly negatively associated with per-touch efficiency but are strongly predictive of total yardage and per-game production.

The correlation matrix and heatmap allow for quick visual identification of relationships among variables. It also highlights which metrics can serve as robust predictors of total output and which might be less sensitive to workload changes.

3.5 Outlier Identification

Finally, RBs with extreme workloads or unusually high efficiency were examined to identify potential outliers.

Figure 14: RBs with >400 Total Touches

1	Chris Johnson	2009	408	2509	6.1
2	Christian McCaffrey	2019	403	2392	5.9
3	Tiki Barber	2005	411	2390	5.8
4	LaDainian Tomlinson	2003	413	2370	5.7
5	Steven Jackson	2006	436	2334	5.4
6	LaDainian Tomlinson	2006	404	2323	5.8
7	Edgerrin James	2000	450	2303	5.1
8	Jamal Lewis	2003	413	2271	5.5
9	DeMarco Murray	2014	449	2261	5
10	Ahman Green	2003	405	2250	5.6

Figure 14 displays a table listing RBs exceeding 400 touches in a single season. These high-touch seasons are rare and often correspond to historically dominant players.

Figure 15: RBs with >8.0 Yards per Touch

	Player	Season	Scrimmage_Touch	Scrimmage_YScm	Scrimmage_Y.Tch
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
1	Amp Lee	1997	89	929	10.4
2	Roy Helu	2014	82	693	8.5
3	Ronnie Harmon	1996	71	619	8.7
4	Mewelde Moore	2006	70	599	8.6
5	Brian Mitchell	1997	59	545	9.2
6	Dexter McCluster	2012	64	522	8.2
7	Ty Johnson	2024	59	497	8.4
8	Keaton Mitchell	2023	56	489	8.7
9	Mike Goodson	2012	51	416	8.2

Figure 15 is a table highlighting RBs with exceptionally high efficiency. These outliers demonstrate the potential for extraordinary performance under moderate or high workloads.

These outliers, while uncommon, are important for understanding the range of RB performance and the potential influence of exceptional seasons on average metrics.

3.6 Sources of Error, Uncertainty, and Bias

Several potential sources of error or bias were considered in this analysis. First, while the data was scraped from Pro-Football-Reference, a widely used and generally reliable source, any inaccuracies in the original tables could propagate through the analysis. Second, the dataset was filtered to exclude RBs with fewer than 50 touches, which ensures focus on meaningful workloads but may omit backup or situational players, potentially biasing the sample toward higher-performing athletes. Third, seasonal variability in offensive strategies, team composition, and rule changes may influence workload and efficiency comparisons across years. Finally, derived metrics such as touches per game assume consistent performance within a season, which could obscure game-to-game variation. Despite these considerations, the exploratory analysis provides a comprehensive examination of RB workloads, efficiency, and trends, forming a solid foundation for modeling and hypothesis testing in subsequent sections.

4. Hypothesis Testing, Model Development and Application

This section presents the modeling approaches applied to understand the relationship between NFL running back (RB) workload and efficiency. Multiple methods were developed, including hypothesis testing, linear regression, and unsupervised clustering. These models serve complementary purposes- regression models quantify how workload and other predictors influence yards per touch, while clustering identifies natural groupings of RBs based on workload and efficiency characteristics. All models were evaluated for performance, and visualizations were used to illustrate and guide model selection and interpretation.

4.1 Hypothesis Testing of Workload Groups

To formally test whether workload affects RB efficiency, statistical hypothesis testing was performed. RBs were grouped using two approaches, as described previously. First, RBs were split relative to the median total touches (152), producing “Above Median” and “Below Median” groups. Welch's t-test revealed a statistically significant difference in yards per touch between these groups: RBs above the median averaged 4.72 yards per touch, while below-median RBs averaged 4.86 (t = −3.46, df = 1877, p = 0.00056), indicating a modest decrease in per-touch efficiency for higher workloads.

Next, RBs were grouped using a fixed threshold of 300 touches to identify "High" and "Low" workload RBs. For this grouping, Welch's t-test indicated no statistically significant difference in efficiency: RBs with more than 300 touches averaged 4.79 yards per touch, identical to RBs below 300 touches (t = 0.037, df = 479, p = 0.97). This suggests that among extremely high-volume RBs, efficiency remains largely consistent with lower-volume peers.

Overall, these results reinforce the earlier observation that moderate increases in workload can slightly reduce per-touch efficiency, but extremely high workloads do not necessarily exacerbate this effect.

Figure 16: Welch's t-Test Output for Median Workload Group

```
 estimate estimate1 estimate2 statistic  p.value parameter conf.low conf.high method                  alternative
    <dbl>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>    <dbl>     <dbl> <chr>                   <chr>
   -0.134      4.72      4.86     -3.46 0.000557     1877.   -0.210   -0.0580 Welch Two Sample t-test two.sided
```

Figure 16 displays the mean efficiency, standard deviation, t-statistic, degrees of freedom, and p-value for RBs above and below the median total touches.

Figure 17: Welch's t-Test Output for Fixed 300-Touch Threshold

```
 estimate estimate1 estimate2 statistic p.value parameter conf.low conf.high method                  alternative
    <dbl>     <dbl>     <dbl>     <dbl>   <dbl>     <dbl>    <dbl>     <dbl> <chr>                   <chr>
  0.00166      4.79      4.79    0.0373   0.970      479.  -0.0860    0.0893 Welch Two Sample t-test two.sided
```

Figure 17 displays the mean efficiency, standard deviation, t-statistic, degrees of freedom, and p-value for RBs above and below the fixed amount of total touches.

The tables clearly show the statistical significance of efficiency differences across workload groups, even if the absolute difference in mean yards per touch is modest. These results provide quantitative evidence that heavier workloads are slightly associated with reduced per-touch productivity, supporting the observations from preliminary exploratory analysis. Importantly, the outputs also highlight the sample sizes and variability within each group, emphasizing that while the effect exists, efficiency remains largely consistent across the majority of RBs.

4.2 Linear Regression Models

To explore the predictive relationship between workload and efficiency, a linear regression model was developed with total touches (Scrimmage_Touch) as the sole predictor of yards per touch (Scrimmage_Y.Tch). The model indicates a small but statistically significant negative effect of total touches on efficiency ($\beta = -0.0004566$, $t = -2.273$, $p = 0.023$), suggesting that as workload increases, yards per touch slightly decrease. However, the model explains very little of the variance in efficiency ($R^2 = 0.0024$, Adjusted $R^2 = 0.0019$), meaning that touches alone are not a strong predictor of per-touch productivity. Residuals range from −2.53 to 5.57, with a median close to zero, and plotting residuals versus fitted values shows no obvious violations of linearity or heteroscedasticity. Figures 18 and 19 illustrate the scatter plot with the regression line and the residuals versus fitted values, respectively. Overall, while total touches have a measurable effect, additional variables would be necessary to more fully model RB efficiency.

Figure 18: Model 1 Scatter Plot of Yards per Touch vs Total Touches

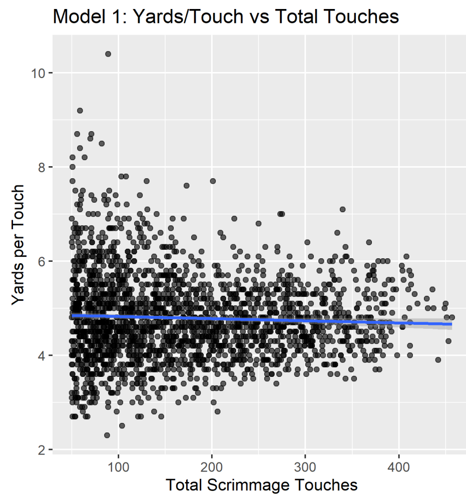


Figure 18 depicts a scatter plot with regression line showing a slight downward trend in efficiency as total touches increase.

Figure 19: Model 1 Residuals vs Fitted Values

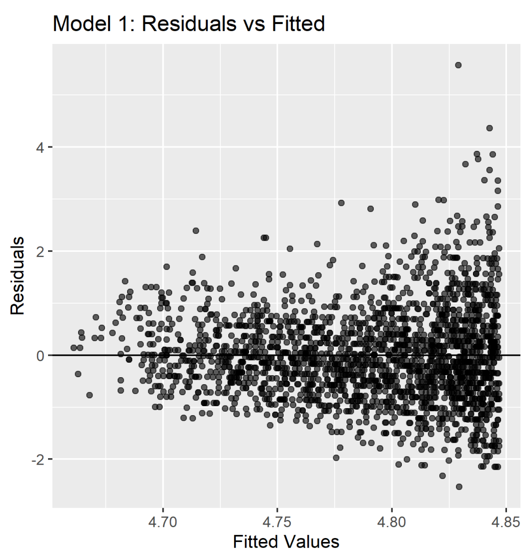


Figure 19 is a plot indicating approximate homoscedasticity and linearity, with no strong patterns in residuals.

Building on the initial simple regression, Model 2 incorporated multiple predictors, including total touches (Scrimmage_Touch), age (Age), yards per game (yards_per_game), and touches per game (touches_per_game) in a multiple linear regression framework. This model substantially improved explanatory power ($R^2 = 0.7656$, Adjusted $R^2 = 0.7652$), indicating that these combined features capture the major sources of variability in RB efficiency. The results show that age had a small positive effect on yards per touch ($\beta = 0.00796$, $t = 2.376$, $p = 0.018$), yards per game was strongly positive ($\beta = 0.0750$, $t = 81.718$, $p < 2e\text{-}16$), and touches per game had a strong negative effect ($\beta = -0.364$, $t = -71.700$, $p < 2e\text{-}16$). Interestingly, total touches became nonsignificant in this context ($\beta = -0.000184$, $t = -0.850$, $p = 0.395$), suggesting that efficiency is better explained by per-game workload and productivity rather than raw seasonal volume.

Residuals ranged from −1.71 to 3.15, with a median near zero. The residual plot (Figure 21) exhibits a slight bowtie pattern, indicating that variance increases with fitted values. While the linear model captures the primary relationships, this heteroscedasticity suggests that inferences using standard errors may be affected, and robust standard errors or alternative modeling approaches could further improve reliability. Figures 20 and 21 display the scatter plot with the regression line and residuals versus fitted values, respectively, highlighting the improved model fit and overall predictive performance compared to the simple regression.

Figure 20: Model 2 Scatter Plot of Yards per Touch vs Total Touches

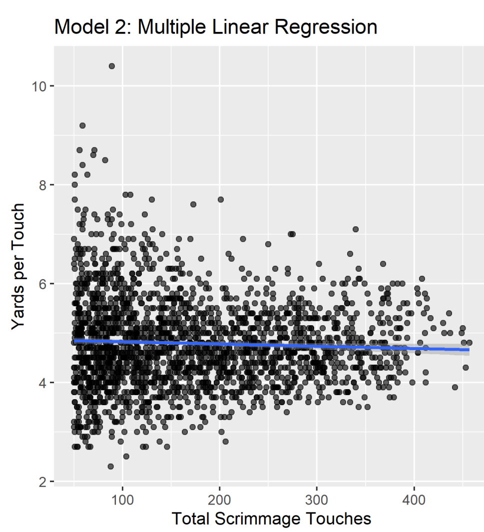


Figure 20 depicts a scatter plot with regression line from multiple linear regression model. The line shows a near-flat trend due to the stronger effects of other predictors.

Figure 21: Model 2 Residuals vs Fitted Values

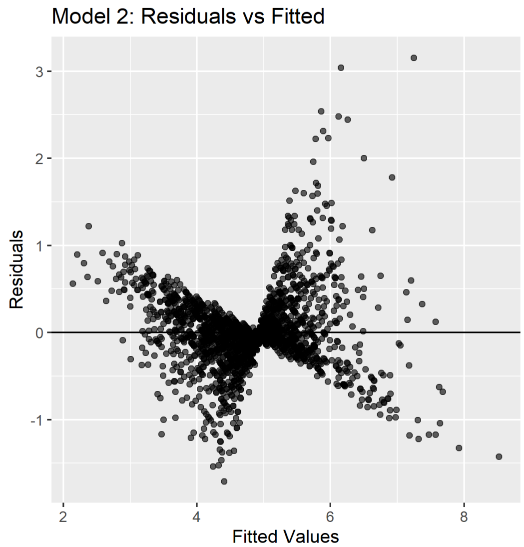


Figure 21 is a residual plot illustrating more uniform spread and smaller residuals compared to Model 1, confirming improved predictive performance.

An alternative model, Model 3, examined age and yards per game as predictors while excluding total touches and touches per game. The results indicated that older RBs exhibited a slight decrease in efficiency ($\beta = -0.0222$, $t = -3.297$, $p = 0.001$), while yards per game remained strongly predictive ($\beta = 0.00549$, $t = 8.716$, $p < 2e\text{-}16$). This model had much lower explanatory power ($R^2 = 0.039$, Adjusted $R^2 = 0.038$), indicating that age alone explains only a small portion of the variation in efficiency. Residuals ranged from −2.29 to 5.63. In Figure 22, the scatter plot appears to show vertical "pillars," which is a consequence of age being recorded as integer values (RB ages fall directly on whole numbers like 25, 26, 27, etc. rather than continuous values), causing multiple points to align vertically. Figure 23 presents the residuals versus fitted values, illustrating that Model 3 captures far less variability compared to Model 2.

Figure 22: Model 3 Scatter Plot of Yards per Touch vs Age

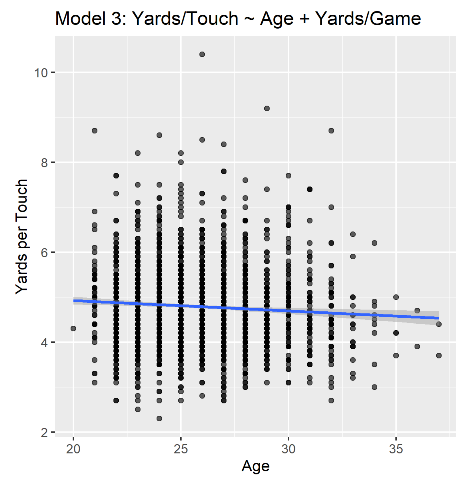


Figure 22 depicts a scatter plot showing modest downward trend in efficiency with increasing age.

Figure 23: Model 3 Residuals vs Fitted Values

Residual plot showing wider spread of residuals than Model 2, consistent with lower model explanatory power.

Overall, the regression analysis indicates that RB efficiency is influenced by multiple factors, with per-game workload and productivity measures (yards per game and touches per game) being the strongest predictors. While total seasonal touches alone have a small negative effect on efficiency, this effect becomes nonsignificant once other variables are included, highlighting the importance of context in evaluating workload. Model 2 provides the best explanatory power, though the slight bowtie pattern in the residuals suggests some heteroscedasticity, meaning variance in efficiency increases at higher fitted values. Model 3 demonstrates that age alone explains only a small portion of variability, and the apparent vertical “pillars” in Figure 22 reflect the integer nature of recorded ages rather than a modeling artifact. Collectively, these results emphasize that RB efficiency is multifactorial, and future modeling could benefit from additional predictors or heteroscedasticity-robust approaches to more accurately capture variation in performance.

4.3 K-Means Clustering

In addition to predictive regression models, unsupervised clustering was employed to identify natural groupings of RBs based on workload and efficiency. Features used for clustering included total touches, yards per touch, and yards per game. The data were standardized before clustering, and k-means was applied with k values ranging from 2 to 8. Evaluation metrics included total within-cluster sum of squares (WCSS) and average silhouette width.

Figure 24: Elbow Method for K-Means Clustering

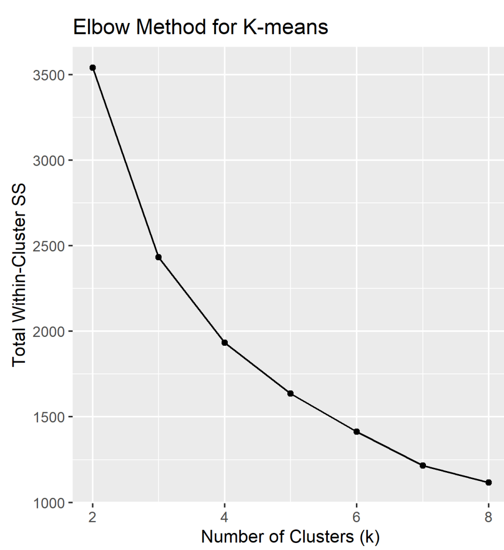


Figure 24 shows a line plot of WCSS versus number of clusters. There doesn’t appear to be a clear elbow, though the most pronounced bend occurs at k = 4.

Figure 25: Average Silhouette Width by Number of Clusters

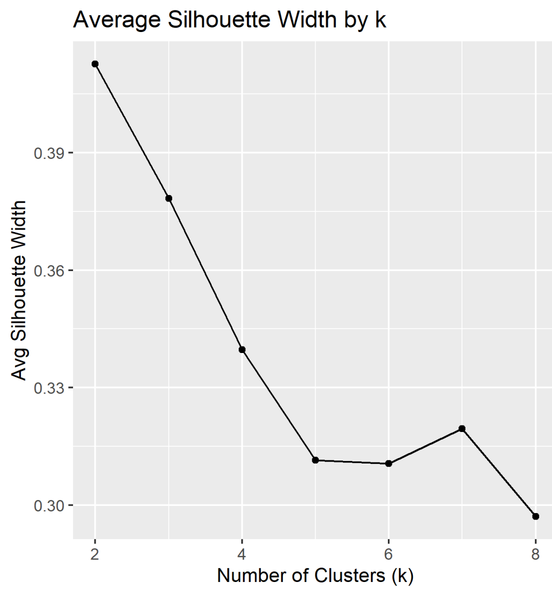
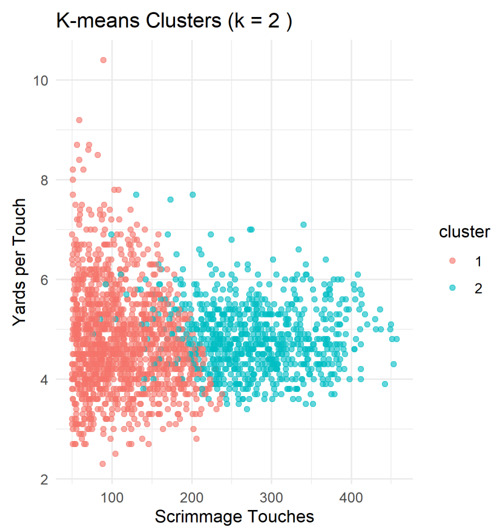


Figure 25 depicts a line plot of average silhouette width, indicating the highest average silhouette for k = 2, suggesting two well-separated clusters.

Figure 24 shows the elbow plot, with a noticeable inflection at k = 4, suggesting diminishing returns in WCSS reduction beyond this point. However, Figure 25 presents silhouette widths, indicating that k = 2 provides the best balance between cluster cohesion and separation.

The final k-means model with k = 2 revealed two clusters of RBs: Cluster 1 (n = 1,349) contained players with moderate touches and efficiency, while Cluster 2 (n = 800) included higher-touch or higher-yards-per-touch RBs. Figure 26 shows a 2D scatter plot of these clusters based on total touches and yards per touch, illustrating clear separation. Silhouette analysis for the final model (Figure 27) confirmed reasonable cluster cohesion, with average silhouette widths of 0.40 for Cluster 1 and 0.43 for Cluster 2. These clusters suggest that RBs can be meaningfully grouped by workload and efficiency, providing additional insight into typical and high-usage player profiles.

Figure 26: K-Means Clusters (k = 2) of RBs



Scatter plot of RBs grouped by k-means clustering, colored by cluster, showing separation based on workload and efficiency.

Figure 27: Silhouette Plot for Final K-Means Model

Silhouette plot displaying cluster quality, with positive silhouette widths confirming reasonable cluster separation.

4.4 Model Performance and Validation

Model validation was conducted using standard regression diagnostics and cluster quality metrics. For the regression models, residual analysis confirmed approximate linearity and no major violations of assumptions, though Model 2 exhibited a slight bowtie pattern in residuals, suggesting mild heteroscedasticity, and Model 3 displayed vertical “pillars” due to integer age values. Model 2 explained a substantial portion of variance in efficiency ($R^2 = 0.7656$), providing high predictive confidence, whereas Model 1 and Model 3 explained far less.

For clustering, silhouette widths and WCSS guided the selection of k, ensuring meaningful separation between RB groups. The final k = 2 model produced well-defined clusters with average silhouette widths of 0.40 and 0.43, confirming reasonable cohesion and separation.

Together, these analyses demonstrate that while regression models capture predictors of individual RB efficiency, clustering highlights natural groupings in workload and performance. This combination provides a robust view of RB patterns, suggesting that per-game performance and yards accumulation are stronger determinants of efficiency than raw seasonal touches.

5. Conclusion and Discussion

This study investigated the relationship between workload and efficiency among NFL running backs using nearly three decades of scrimmage statistics. The analysis combined exploratory data visualization, hypothesis testing, linear regression modeling, and unsupervised clustering to examine how total touches, per-game averages, age, and productivity contribute to efficiency, measured in yards per touch. Initial expectations were that heavier workloads would meaningfully reduce per-touch efficiency. However, the findings indicate that this effect is modest at best. The preliminary analysis showed that most running backs cluster around 4–5 yards per touch regardless of workload level, and the correlation between total touches and efficiency was near zero. Hypothesis testing confirmed these patterns. While RBs above the median workload exhibited a statistically significant but small decrease in efficiency, extremely high-volume players (300+ touches) did not differ meaningfully from others in yards per touch. This suggests that high-workload running backs are likely to maintain efficiency because teams tend to concentrate touches on their most durable, well-conditioned, and consistently productive players.

Regression modeling provided further insight into the drivers of efficiency. A simple linear model using total touches as the sole predictor revealed a statistically significant but practically negligible negative effect, explaining almost none of the variance. In contrast, the multiple regression model incorporating touches per game, yards per game, and age substantially improved explanatory power, with over 76% of the variance in efficiency accounted for. These results highlight that per-game context and overall productivity, rather than raw seasonal volume, are the primary determinants of per-touch efficiency. The alternative regression model focusing on age and yards per game demonstrated the limited explanatory power of age alone, reinforcing the notion that efficiency is driven more by situational factors than by player demographics.

Unsupervised clustering provided another perspective by identifying natural groupings among players. The final k-means model (k = 2) revealed two broad RB profiles. The first was a large group characterized by moderate workloads and efficiency. The second group consisted of players with higher total touches or elevated per-touch averages. These clusters aligned with patterns detected in earlier sections. These clusters aligned with patterns detected in earlier sections, reinforcing the notion that running backs tend to fall into distinct usage archetypes shaped by team strategy, player durability, and offensive design.

As the project progressed, several analytical decisions were changed and refined. The decision to exclude RBs with fewer than 50 touches removed extreme outliers and ensured more meaningful comparisons. Derived metrics such as touches per game and yards per game proved essential for modeling, revealing that simple season totals obscure variance. The discovery of mild heteroscedasticity and the vertical “pillar” age structure prompted adjustments in interpretation, particularly when evaluating model assumptions. If the project were extended, future work could incorporate injury histories, offensive line metrics, or team offensive strategies, all of which may help explain remaining variance in efficiency. Nonlinear modeling approaches or hierarchical models could also address the residual variance patterns observed in the multiple regression model.

Overall, this study concludes that NFL running back efficiency is stable across a wide range of workloads. While heavier usage may slightly reduce per-touch productivity, this effect is small and overshadowed by more influential factors such as per-game workload and total yardage accumulation. The findings contribute to a deeper understanding of how running backs are utilized in modern NFL offenses and provide a foundation for future research exploring the interplay between workload, efficiency, durability, and long-term performance.

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