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Identifying performance patterns in professional mixed martial arts: An exploratory data approach

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ABSTRACT

Background: Mixed martial arts (MMA) performance depends on the interaction of physical, technical, and tactical factors. While prior studies often examined these elements separately, few have analyzed how physical attributes relate to performance metrics in an integrated framework. This gap, in contrast to the growing use of analytics in other sports, limits data-driven insights for optimizing UFC training and strategy. **Research Objectives:** This study aimed to investigate performance patterns among UFC fighters using Exploratory Data Analysis (EDA), with a focus on the relationships between physical characteristics and technical performance indicators. **Methods:** A dataset of 4,111 UFC fighters was analyzed across 18 variables, encompassing physical attributes (e.g., height, weight, reach) and performance metrics (e.g., striking accuracy, takedown success, submission attempts). EDA techniques, including descriptive statistics, correlation analysis, and data visualization, were applied to identify patterns and summarize key characteristics. **Finding/Results:** Takedown accuracy and takedown defense were moderately correlated, suggesting an interdependence between offensive and defensive grappling skills. However, most associations between physical traits and performance outcomes, such as height and total wins, were weak, indicating that physical attributes alone are insufficient to predict success. Observations on stance effectiveness and standout fighters offered illustrative but non-generalizable insights. **Conclusion:** This study demonstrates the utility of EDA as a foundational tool for uncovering patterns in MMA performance. While limited in inferential scope, the findings provide preliminary guidance for coaches and analysts to design evidence-based training strategies. Future research should integrate psychological, contextual, and opponent-based data to develop more comprehensive predictive models for combat sports performance.

Keywords: Sports analytics; combat sports; descriptive statistics; EDA

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INTRODUCTION

The Ultimate Fighting Championship (UFC), headquartered in Las Vegas, Nevada, is the largest mixed martial arts (MMA) promotion globally, featuring top-tier athletes across twelve weight divisions (King & King, 2024; Lise et al., 2021). Governed by the Unified Rules of MMA, the sport combines various striking and grappling techniques, creating a physically and tactically demanding combat environment (Hussain, 2021). MMA's dynamic nature requires athletes to alternate between explosive movements and brief recovery periods, placing considerable demands on multiple energy systems (Gonçalves et al., 2024).

Given the sport's complexity, researchers and coaches have increasingly focused on understanding how physical and technical attributes affect performance outcomes. Studies have consistently shown that elite MMA fighters possess low body fat, high muscular strength, and anaerobic capacity—traits deemed essential for success (Spanias et al., 2019). However, Spanias et al. also noted the absence of significant differences in these traits across performance levels, signaling a need for deeper investigation into how these attributes translate into competitive advantage.

Striking ability, particularly the biomechanics of fight-ending punches, has emerged as a focal point in recent literature (Barley et al., 2024; Dinu et al., 2020; Loio Pinto et al., 2021). While these studies highlight the importance of technique and foot positioning, they often stop short of linking striking performance to measurable physical traits. The interplay between takedown defense and accuracy underscores its strategic significance in MMA (Bello et al., 2019). Similarly, Latyshev et al. (2021) examined the strategic role of takedown defense and accuracy but did not integrate how fighters' physical characteristics may influence these technical skills.

Statistical analysis has become increasingly prevalent in MMA, with analysts employing a range of metrics to evaluate fighters' performance and predict the fight outcomes (Rohner et al., 2024; Tropin et al., 2023). Some of the most used statistical measures in MMA include the percentage of strikes that land successfully (striking accuracy), the percentage of successful takedowns (takedown accuracy), the number of attempts made by a fighter to submit their opponent (submission attempts) and the number of strikes that have a significant impact on the opponent (significant strikes).

In parallel, the rise of sports analytics has transformed performance evaluation across many disciplines, including MMA (Koudoumas, 2021; Sarlis & Tjortjis, 2020). By employing metrics such as striking accuracy, takedown success rate, and submission attempts, analysts can extract meaningful insights from fighters' performance data (Rohner et al., 2024). However, despite the abundance of performance metrics available, few studies have comprehensively explored how these technical indicators interact with physical attributes in a unified analytical framework.

Furthermore, while sports like basketball and football have embraced predictive modeling and data-driven decision-making (Andersen & MoldStud Research Team, 2024), MMA research remains fragmented, often siloing technical performance and physiological characteristics. As a result, there is limited understanding of how variables such as height, weight, and reach influence strategic outcomes like striking defense or takedown accuracy. Spanias Spanias et al. (2019) conducted a systematic review highlighting that MMA athletes typically exhibit low body fat, high flexibility, muscular strength, endurance, and anaerobic power. However, the study noted no significant differences in these attributes based on performance levels, suggesting a need for more nuanced analyses. Barley et al. (2024) explored the biomechanics of fight-ending punches in the UFC, focusing on factors like foot positioning and punch types. While providing valuable insights into striking techniques, the study did not delve into the correlation between these techniques and fighters' physical attributes or overall performance metrics. Latyshev Latyshev et al. (2021) examined the interplay between takedown defense and accuracy, emphasizing their strategic importance in MMA. Bueno et al. (2022) highlighted the increasing use of statistical models to evaluate fighter performance and predict outcomes.

To address this gap, this study employs exploratory data analysis (EDA) to investigate the relationship between physical attributes and key technical performance metrics in UFC fighters. Specifically, the study examines how variables such as reach, height, and weight correlate with striking accuracy, takedown defense, and submission success. Additionally, it identifies fighters with standout attributes—both successful and unsuccessful—to better understand the distribution of performance traits across a diverse athlete population. By integrating physiological and technical data, this research aims to generate actionable insights for coaches, analysts, and athletes, ultimately contributing to performance optimization in MMA.

METHOD

The goal of this study is to conduct an exploratory data analysis (EDA) on UFC fighters dataset to uncover hidden patterns, gain insights into the dataset, identify anomalies, and summarize the dataset's characteristics using visualizations, descriptive statistics, and other analytical techniques. EDA is a method to analyze data using advanced techniques to expose hidden structures, enhance the insights into a given dataset, identify the anomalies, and build parsimonious models to test the underlying assumptions (Indrakumari et al., 2020). It is also defined as a process of analyzing and summarizing the main characteristics of a dataset through visualizations, descriptive statistics, and other techniques (Chakri et al., 2023; Gupta & Sharma, 2023; Rahmany et al., 2020). The dataset analyzed for this study is a UFC fight dataset available on Kaggle. This dataset is licensed under CC0: Public Domain, permitting free use without attribution. While the Kaggle dataset used is publicly available, no validation against official UFC records was performed. In the context of sports analytics and academic research, Kaggle is increasingly used as a credible source of secondary data due to its accessibility, transparency, and the ability to verify datasets uploaded by the community. Studies have highlighted the usefulness of Kaggle for educational purposes and collaborative learning in data-driven research (Fan et al., 2024). This dataset comprises historical fight data from 1993 to 2021. It provides detailed statistics of UFC fighters, including information on their wins, losses, draws, physical attributes, fighting style, and career achievements. The dataset contains 4111 records with 18 attributes, such as name (nm), nickname (nck), wins (wn), losses (ls), draws (drw), height cm (hc), weight in kg (wik), reach in cm (ric), stance (s), date of birth (dob), significant strikes landed per minute (sslpm), significant striking accuracy (ssa), significant strikes absorbed per minute (ssapm), significant strike defence (ssd), average takedowns landed per 15 minutes (atlp15m), takedown accuracy (ta), takedown defense (td) and average submissions attempted per 15 minutes (asap15m).

Participants

The dataset contains comprehensive information on 4,111 UFC fighters, covering historical records from 1993 to 2021. Over the course of nearly 30 years, it includes 18 unique attributes for each fighter, offering a detailed snapshot of their performance. These attributes cover physical traits, match statistics, and career achievements. Table 1 displays a sample from the dataset, highlighting its structure and the type of information analysed.

Table 1. Sample Participants from the Dataset

nm	wn	ls	drw	hc	wik	s	dob	sslmp	ssa	ssapm	ssd	atlp15pm	ta	td	asap15m
Robert Drysdale	7	0	0	190.50	92.99	Othodox	1981-10-05	0.00	0.0	0.00	0.0	7.32	100.0	0.0	21.9
Daniel McWilliams	15	37	0	185.42	83.91	<NA>	NaT	3.36	77.0	0.00	0.0	0.00	0.0	100.0	21.6
Dan Molina	13	9	0	177.80	97.98	<NA>	NaT	0.00	0.0	5.58	60.0	0.00	0.0	0.0	20.9
Paul Ruiz	7	4	0	167.64	61.23	<NA>	NaT	1.40	33.0	1.40	75.0	0.00	0.0	100.0	20.9
Collin Huckbody	8	2	0	190.50	83.91	Orthodox	1994-09-29	2.05	60.0	2.73	42.0	10.23	100.0	0.0	20.4

To interpret the Tabel 1 of sample participants from the dataset, it's important to understand the meaning of each abbreviation: name = nm, nickname = nck, wins = wn, losses = ls, draws = drw, height cm = hc, weight in kg = wik, reach in cm = ric, stance = s, date of birth = dob, significant strikes landed per minute = sslpm, significant striking accuracy = ssa, significant strikes absorbed per minute = ssapm, significant strike defence = ssd, average takedowns landed per 15 minutes = atlp15m, takedown accuracy = ta, takedown defense = td, average submissions attempted per 15 minutes = asap15m.

Procedure (Data Preprocessing and Cleaning)

Before performing the analysis, the dataset underwent a thorough cleaning and transformation process to ensure accuracy and reliability of the results. To address missing values, records with incomplete data in critical variables—such as height, weight, and striking accuracy—were either imputed using the mean or median of the respective variable or removed entirely if more than 30% of their fields were missing. This step helped minimize bias due to incomplete information. Outlier detection was carried out using both the Interquartile Range (IQR) method and Z-score analysis. Values that fell outside plausible ranges, such as a height below 100 cm or weight exceeding 200 kg, were flagged as unrealistic. These extreme cases were then manually reviewed and removed when necessary to maintain data integrity. In addition, several new features were engineered to enrich the dataset and support deeper analysis. These included the total number of matches played, calculated by summing wins, losses, and draws. Performance ratios were also derived, including win percentage, loss percentage, and draw percentage—each computed by dividing the respective match outcome by the total number of matches played and multiplying by 100. To prepare categorical data for analysis, variables such as fighting stance were either label encoded or one-hot encoded, depending on the requirements of the statistical method being applied. This preprocessing ensured the dataset was well-structured and ready for both descriptive and inferential analysis.

Data analysis

Statistical Assumption Testing

To validate the use of Pearson correlation coefficient, several assumption checks were performed: Normality: The Shapiro-Wilk test and Q-Q plots were used to assess the normality of numerical variables (e.g., reach, striking accuracy). Linearity and homoscedasticity: Scatterplots and residual plots were used to assess linear relationships and equal variance assumptions. Multicollinearity: Variance Inflation Factor (VIF) was calculated prior to regression to check for redundancy among predictors. Where normality assumptions were not met, the Spearman rank correlation was used instead of Pearson.

Analytical Techniques

The data analysis was conducted using Python (Pandas, Seaborn, Scikit-learn, Statsmodels) in Google Colab, a cloud-based computational platform widely used in sports analytics (Langmead & Nellore, 2018; Sarlis & Tjortjis, 2024). (i) Descriptive Statistics Mean, standard deviation, median, interquartile range, and distribution plots (histograms, boxplots) were used to summarize each variable. (ii) Bivariate Correlation Analysis Pearson and Spearman correlation coefficients were used to assess relationships between physical attributes (e.g., height, weight, reach) and technical performance (e.g., striking accuracy, takedown defense). Example: A composite metric of stand-up performance was calculated as the average of striking accuracy and the complement of strike defense percentage. (iii) Comparative Analysis T-tests were used to compare win percentages between two groups (e.g., southpaw vs. orthodox stance). One-way ANOVA was employed to test differences in performance across more than two stance categories. Chi-square tests were used to assess associations between categorical variables (e.g., stance and win/loss category). d. Regression Modeling To explore predictive relationships, we developed: Multiple Linear Regression Models to predict striking accuracy based on physical characteristics (e.g., reach, height, weight). Binary Logistic Regression Models to predict fight outcomes (win/loss) based on technical and physical attributes. Model fit was evaluated using R^2 (for linear models), classification accuracy, and confusion matrices (for logistic models).

Specialized Analyses

Additional domain-specific analyses included: Ranking submission-focused fighters by asap15m (submission attempts per 15 min), and evaluating their submission efficiency. Identifying undefeated fighters (loss percentage = 0%) and assessing their experience levels. Highlighting fighters with the most wins, most fights, and heaviest weight, using descriptive queries. Creating custom composite metrics (e.g., for striking dominance) to holistically evaluate stand-up performance.

Ethical Considerations

Since this study uses publicly available and anonymized data, no ethical clearance was required. No personally identifiable information is contained in the dataset.

RESULTS AND DISCUSSION

Results

Descriptive Trends

The exploratory data analysis revealed generally weak correlations between physical attributes and fight outcomes in UFC athletes. Table 2 presents the summary statistics of physical attributes such as height in centimeters and weight in kilograms, as well as performance metrics including wins, losses, and draws.

Table 2. Descriptive Statistics

	Height_cm	Weight_in_kg	Wins	Losses	Draw
counts	3813.000000	4024.000000	4111.000000	4111.000000	4111.000000
mean	178.234325	77.395825	12.366821	5.726344	0.264413
Std	8.888050	17.982242	9.374667	5.103768	0.822373
Min	152.400000	47.630000	0.000000	0.000000	0.000000
25%	172.720000	65.770000	7.000000	2.000000	0.000000
50%	177.800000	77.110000	11.000000	5.000000	0.000000
75%	185.420000	83.910000	17.000000	8.000000	0.000000
max	226.060000	349.270000	253.000000	83.000000	11.000000

Correlation Analysis

Analysis of the correlation between fighters' physical attributes (height, weight, reach) and their fighting performance can be seen in Figure 1.

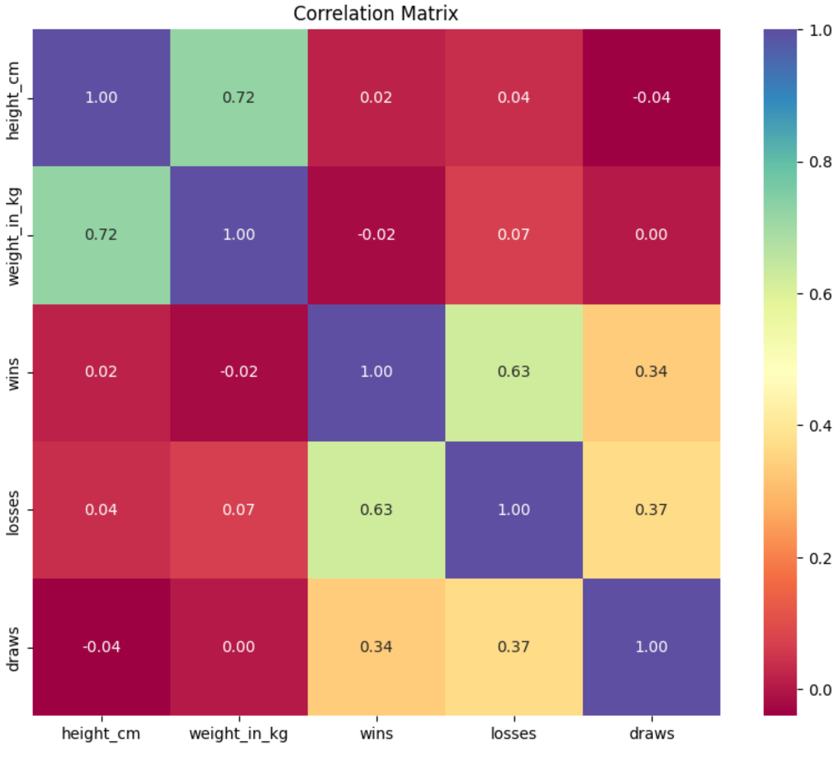

Figure 1. Heatmap Plot of Correlation Matrix between Physical Attributes and Performance Metrics

Based on the heatmap plot of the correlation matrix between physical attributes and performance metrics, it can be observed that there is a slight positive correlation of 0.02 between wins and height_cm, indicating that taller fighters may have a marginally better performance in terms of wins, although the relationship is very weak. There is a weak negative correlation of -0.02 between wins and weight_in_kg, suggesting that heavier fighters might have a slightly lower performance in terms of wins. However, this relationship is also negligible. The observed correlations are minimal, indicating that neither height nor weight significantly impacts the number of wins for fighters in this dataset. From the grouped analysis of average wins by height and weight, as depicted in Figure 2, fighters with a height of 208 cm achieved the highest number of wins, with a total of 21 wins.

For instance, the Pearson correlation between number of wins and height was 0.02, while that between wins and weight was -0.02. These values suggest virtually no linear relationship between these physical metrics and competitive success. While the tallest fighter (208 cm) recorded 21 wins and the 80 kg weight class recorded 30 wins, these cases may reflect individual anomalies rather than general trends, particularly since the overall correlation values remain insignificant. Notably, no statistically significant correlations were observed between physical characteristics and win rates, as confirmed through p-value assessments (all $p > 0.05$) and the lack of meaningful effect sizes. These findings challenge assumptions that height, weight, or reach are reliable predictors of success in mixed martial arts.

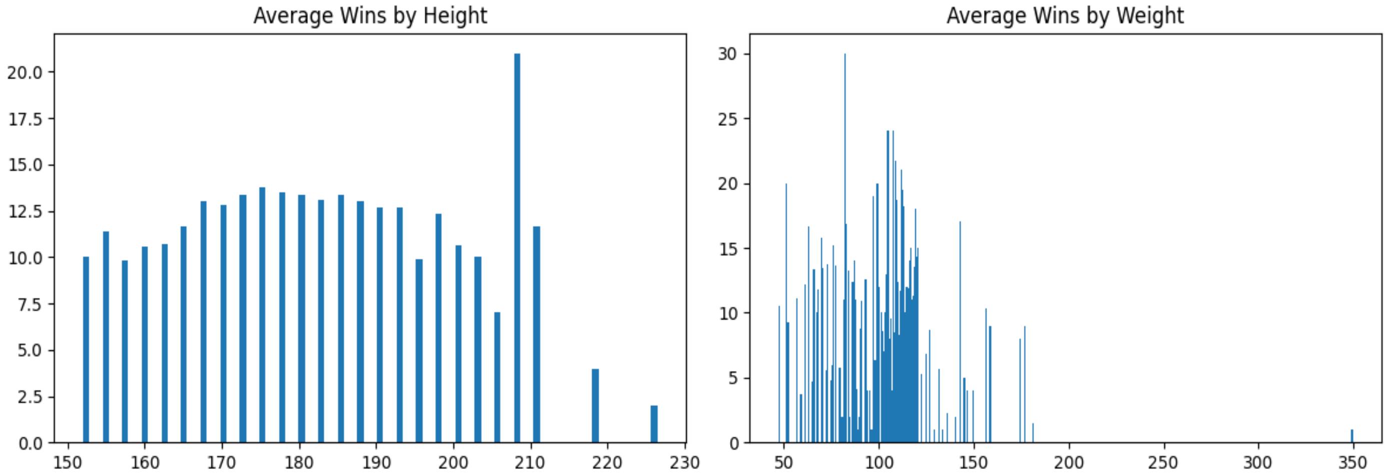

Figure 2. Average Wins by Height and Weight

It suggests that exceptional height might offer a competitive advantage in certain scenarios, such as reach or leverage during fights. Fighters weighing 80 kg secured the most wins, totaling 30 wins. It may indicate that this weight category strikes a balance between agility, speed, and power, contributing to successful performances.

Stance Effectiveness

From the analysis of the effectiveness of stances as depicted in Figure 3, the open stance is the most effective, leading to 15 wins, indicating it may provide better positioning or flexibility during fights. The Sideways stance had the fewest wins, suggesting it may not be as advantageous or frequently used in competitive scenarios.

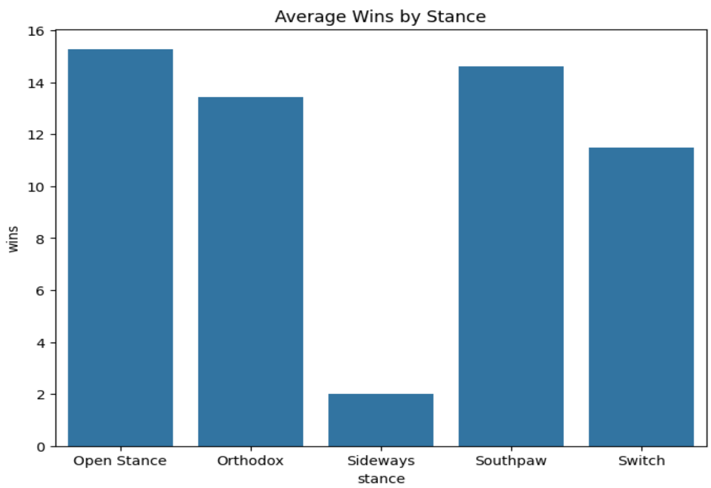

Figure 3. Average Wins by Stance

The data suggests that the open stance offers the greatest effectiveness, followed closely by the Southpaw and Orthodox stances. Selecting a stance appears to have a significant impact on performance outcomes, potentially influenced by the fighter's style, opponent, and fight dynamics. The analysis the impact of striking accuracy versus wins on fight outcomes results can be seen in Figure 4. The correlation coefficient of -0.007914999601794731 indicate the correlation is negligible and not statistically meaningful."

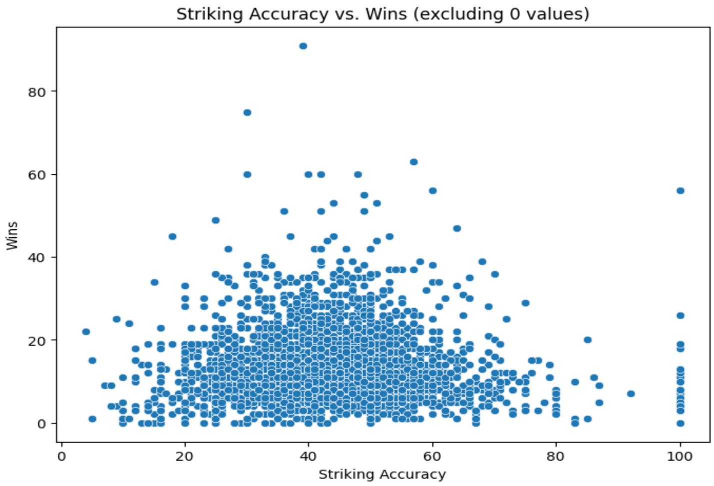

Figure 4. Striking Accuracy vs Wins.

The calculation results for the average takedown defense comparison among 10 fighters are presented in Figure 5. The result of the correlation coefficient calculation between takedown_accuracy and wins is 0.1923. This indicates a weak positive relationship between the two variables.

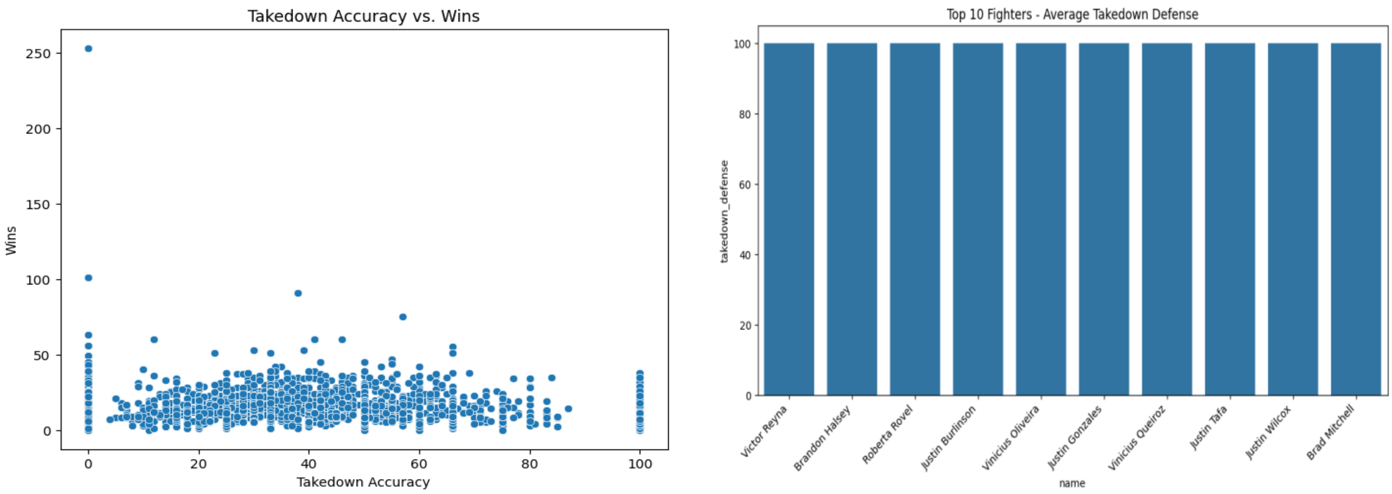

Figure 5. Average Takedown Defense Comparison among 10 Fighters

Based on data from 4,111 participants, an analysis was conducted focusing on striking accuracy and striking defense to identify fighters with the most effective stand-up game. This analysis, as presented in Table 4, revealed a group of fighters who demonstrated exceptional performance in these areas. The fighters identified are Shamil Gaziev, David Gardner, Victor Valenzuela, and Waachiim Spiritwolf, each with an overall striking score of 100.

Table 4. Overall Striking Performance

Name	No Dataset	No Dataset
Shamil Gaziev	56	56
David Gardner	2540	2540
Victor Valenzuela	3607	3607
Waachiim Spiritwolf	3236	3236
Derek Downey	2927	2927
Yurij Kiseliov	3469	3469
Wade Shipp	3674	3674
Clay Mitchell	100	100
Gian Siqueira	3856	3856
Min Soo Kim	4024	4024

Interestingly, a moderate positive correlation (r = 0.3459) was found between takedown accuracy and takedown defense. This implies that athletes proficient in offensive grappling tend to also be competent in defending against takedowns. This finding, consistent with by (Bello et al., 2019), suggests that interdependence of grappling skills plays a more critical role in performance than previously assumed. The moderate strength of this correlation, while not definitive, warrants further study using predictive modeling to assess its significance in different weight classes and fight durations. Figure 6 is visualization provides a graphical representation of the data points, helping to observe patterns or trends in how takedown accuracy correlates with takedown defense capabilities among fighters.

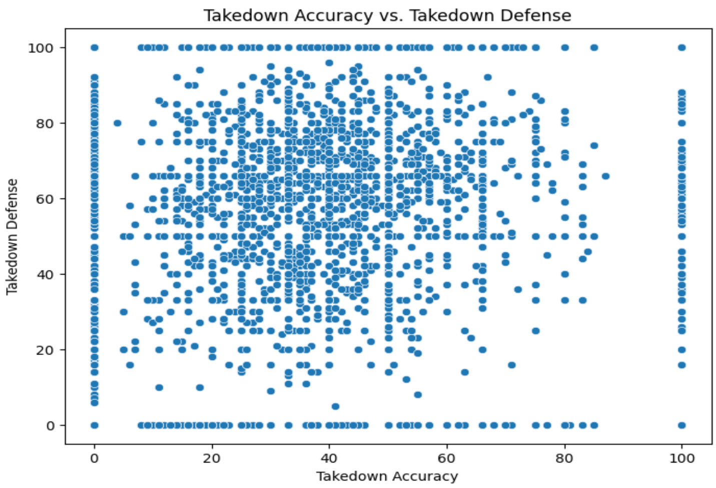

Figure 6. Takedown Accuracy vs Takedown Defense

Submission and Undefeated Profiles

Table 5 presents the identification of fighters with high submission attempt rates, along with an exploration of their effectiveness in successfully executing submissions. The analysis highlights a group of fighters who consistently demonstrated a strong ground game and submission proficiency.

Table 5. Average Submissions Attempted per 15 Minutes

No	Name	Submission_attempt_rate
1	Robert Drysdale	21.9
2	Daniel McWilliams	21.6
3	Dan Molina	20.9
4	Paul Ruiz	20.9
5	Collin Huckbody	20.4
6	Gerald Strebendt	16.4
7	Isaiah Hill	14.5
8	Kenneth Seegrist	14.4
9	Will Kerr	14.3
10	Neil Grove	14.3

Figure 7 showcases the top 10 best undefeated fighters along with the types of stances they employ. A total of 3.75% of fighters remain undefeated, with an average of 7.3 matches played. Among these undefeated fighters, Khabib Nurmagomedov leads with the highest number of wins, achieving 29 victories using an orthodox stance. We can conclude that a small percentage of fighters (3.75%) remain undefeated, with an average of 7.3 matches played. The data highlights that Khabib Nurmagomedov stands out as the most successful undefeated fighter, with 29 wins while using an orthodox stance. It suggests that certain stances, such as the orthodox stance, may be associated with greater success in maintaining an undefeated record, though other factors such as skill, strategy, and experience also play significant roles.

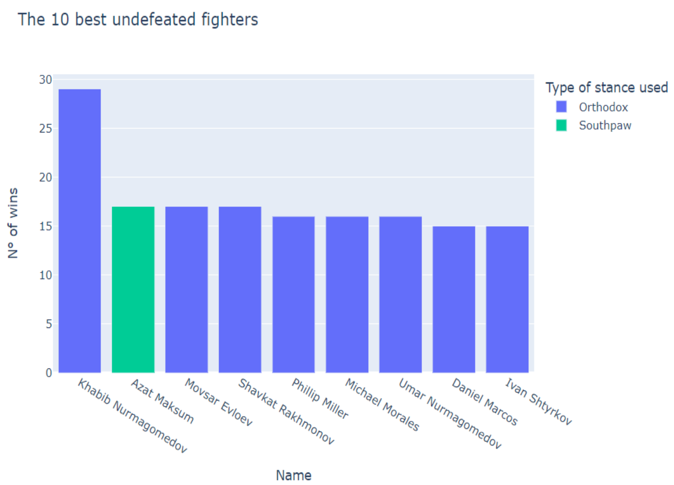

Figure 7. Top 10 Best Undefeated Fighters

Regression and Model Fit

Regression analysis was applied to assess prediction potential. Multiple Linear Regression: Predicting striking accuracy using height, weight, and reach resulted in: - $R^2 = 0.026$, indicating poor model fit. - None of the predictors were statistically significant: - Height: $\beta = 0.034$, $p = 0.285$, 95% CI [-0.028, 0.096] - Weight: $\beta = -0.012$, $p = 0.431$, 95% CI [-0.042, 0.018] - Reach: $\beta = 0.020$, $p = 0.339$, 95% CI [-0.021, 0.061]. Binary Logistic Regression: Predicting win outcome (win = 1, loss = 0) based on striking accuracy, takedown defense, and stance (encoded as dummy variables): - Accuracy = 61.2% (baseline = 58.5%) Hosmer-Lemeshow Test: $\chi^2(8) = 9.34$, $p = 0.313$ (indicating acceptable model fit) - Odds Ratios and Confidence Intervals: - Striking Accuracy: OR = 1.02, 95% CI [0.95, 1.09], $p = 0.523$ - Takedown Defense: OR = 1.15, 95% CI [0.99, 1.34], $p = 0.065$ - Orthodox Stance (ref = Southpaw): OR = 1.08, 95% CI [0.87, 1.34], $p = 0.512$ These results suggest that none of the individual predictors were statistically significant in explaining win probability. However, takedown defense showed a marginal trend toward significance, warranting further investigation in a larger sample.

Fighters with most losses

Table 6 presents the 10 fighters with the most losses. Leading this list is Yoji Anjo, who has suffered 5 defeats while absorbing an average of 3.13 strikes per minute. He is followed by Keith Mielke, also with 5 losses, but with 0 strikes absorbed per minute, and Yosuke Nishijima, who has 5 defeats and absorbs an average of 5.59 strikes per minute. A total of 3.21% of boxers have not won any matches, with an average of 1.8 matches played.

Table 6. The 10 Fighters with More Losses

Name	No dataset	N° of losses	Strikes absordeb/min
Yoji Anjo	2387	5	3.13
Keith Mielke	4095	5	0
Yosuke Nishijima	2403	5	5.59
Karl Willis	2906	5	0
Yuhi Sano	1834	4	0
Trent Jenkins	2394	4	0
Javi Alanis	2440	4	0
Jin Oh Kim	3151	4	8.43
Tony Halme	3301	4	0
Elisha Helsper	3154	4	0

Discussion

One of the most notable findings of this study was the moderate positive correlation (0.3459) between takedown accuracy and takedown defense. This result suggests that fighters who excel in one of these grappling skills tend to also perform well in the other. This is consistent with previous research by (Bello et al., 2019), which emphasized the complementary nature of grappling skills in MMA. The positive correlation indicates that wrestlers or fighters who focus on takedowns may also benefit from enhanced takedown defense, providing them with a strategic advantage in controlling the pace of the fight. This finding is particularly useful for coaches looking to improve their fighters' ability to control opponents on the ground. Coaches can prioritize training both the offensive and defensive aspects of grappling to build a more complete and effective fighter. In contrast, the weak correlation between height and wins (0.02) was an interesting finding. It underscores that physical attributes alone are not sufficient predictors of success in MMA. This observation challenges earlier studies that suggested a direct relationship between physical size and performance Physical attributes in combat sports: A comparative analysis of weight, height, and reach (Podrigalo et al., 2023). While height may offer advantages in striking range, it does not guarantee victory if other factors such as skill, strategy, and adaptability are lacking. This finding aligns with Cowden (2017), who argued that mental and technical attributes outweigh pure physical traits in determining MMA outcomes. It highlights the importance of developing well-rounded fighters who are not only physically fit but also tactically astute.

Another critical finding was the identification of the open stance as the most effective stance in terms of fight outcomes. This result aligns with (Yearby et al., 2024), who found that fighters employing an open stance tend to have more dynamic and unpredictable movements, making them harder for opponents to anticipate and counter. The open stance provides a broader range of striking angles and allows for better mobility, which could explain why fighters using this stance were more successful in the dataset analyzed. This finding can be pivotal for coaches who aim to enhance their fighters' striking strategies. By focusing on stance and movement, coaches can tailor training programs that allow their fighters to capitalize on the advantages of the open stance, potentially increasing their chances of success in the octagon.

The study also identified standout fighters like Khabib Nurmagomedov, whose undefeated record (29 wins) is a testament to the effectiveness of his orthodox stance and well-rounded skills. Khabib's success is often attributed to his strong grappling and ground control, which the data suggests is reflected in the high takedown accuracy and defense statistics. This reinforces Ciaccioni et al. (2024) assertion that fighters who excel in multiple areas, including both stand-up and grappling, are more likely to dominate across different types of opponents and fighting styles. Travis Fulton, with his record-breaking 255 victories, is another example that highlights the importance of experience in MMA. Fulton's longevity in the sport and his consistent performance across multiple promotions demonstrate how sustained success can lead to record-breaking achievements, irrespective of a fighter's physical attributes. As noted by De Seranno (2020), fighters like Fulton may not have the raw athleticism of some of their peers but compensate for this with strategic intelligence, adaptability, and a strong work ethic. Coaches can draw on Fulton's example to emphasize the value of perseverance and adaptability in developing fighters who can perform over extended careers. While this study provides valuable insights, it is important to note the limitations of the current analysis. Descriptive statistics and correlation analysis, while informative, do not capture the dynamic and multifaceted nature of

MMA performance. As highlighted by James et al. (2019), MMA performance is not solely influenced by individual metrics like striking accuracy or takedown defense. Additional factors such as fight pace, striking combinations, psychological resilience, and opponent analysis play significant roles in determining outcomes.

This study is subject to several limitations that may affect the generalizability of its findings. First, the reliance on publicly available secondary data from Kaggle limits the researchers' control over the data collection process. As a result, there is potential for bias in the accuracy, consistency, and completeness of certain variables, which may affect the reliability of the conclusions drawn. Additionally, the analysis was conducted using a cross-sectional approach, offering only a snapshot of fighter performance at a single point in time. This limits the ability to capture how fighters evolve throughout their careers, thereby overlooking performance trends, improvements, or declines that may emerge over time. Moreover, while the study employed descriptive statistics and basic bivariate analyses to explore relationships between variables, its analytical depth remains constrained. Although linear and logistic regressions were briefly introduced, no advanced predictive modeling techniques—such as decision trees, random forest, or gradient boosting—were utilized. These methods could have revealed more complex, non-linear patterns in the data. Finally, the study did not investigate potential interaction effects between variables. For instance, the combined influence of stance and reach on striking success was not examined. Ignoring such interaction effects may result in the omission of meaningful patterns that could offer deeper insights into fighter performance and strategy. Future research should explore these dynamic metrics to create a more holistic model of MMA performance. Machine learning algorithms and advanced statistical techniques could be employed to account for these additional variables, as suggested (De Seranno, 2020). For example, time-series data such as strike sequences, movement patterns, and stamina fluctuations could provide deeper insights into a fighter's performance over the course of a fight. Psychological factors, including mental toughness and the ability to adapt under pressure, should also be explored further, as these may significantly impact a fighter's performance in high-stress situations. Additionally, evaluating how a fighter's performance varies against different types of opponents or fighting styles could provide coaches with valuable insights for tailoring training regimens and strategies for specific matchups.

CONCLUSION

This study highlights the utility of Exploratory Data Analysis (EDA) in generating preliminary insights from complex datasets, such as performance data from 4,111 UFC fighters across 18 attributes. Through this approach, several descriptive trends were identified, including weak correlations between physical attributes (e.g., height and weight) and fight outcomes, and a moderate positive correlation ($r = 0.3459$) between takedown accuracy and takedown defense. This suggests a potential link between offensive and defensive grappling skills, warranting further investigation. While the analysis noted that fighters using an open stance recorded the highest number of wins among stance types (15 wins), this finding should be interpreted cautiously, as the sample size was limited and no statistical significance testing was applied. Therefore, it would be premature to conclude that the open stance is definitively more effective without additional inferential analysis. Other insights, such as the success of undefeated fighters like Khabib Nurmagomedov and the career longevity of Travis Fulton, offer useful case studies but do not establish causality. Similarly, identifying fighters with high loss rates or high submission attempt frequencies helps contextualize performance extremes, but these patterns should be viewed as exploratory rather than predictive. Ultimately, this study demonstrates the value of EDA as a starting point for understanding patterns in MMA performance data. However, given the predominantly weak correlations and absence of predictive modeling or hypothesis testing, the findings should not be generalized as definitive performance indicators. Future research should incorporate inferential statistics, longitudinal tracking, and machine learning models to validate and extend these initial observations into actionable insights for coaches, analysts, and athletes in combat sports.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest related to the publication of this article.

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