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Author: Lachlan P. James Sam Robertson G. Gregory Haff Emma M. Beckman Vincent G. Kelly

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Identifying the performance characteristics of a winning outcome in elite mixed martial arts competition

By

Lachlan P. James [a]

Sam Robertson [b]

G. Gregory Haff [c]

Emma M. Beckman [a]

Vincent G. Kelly [a, d]

[a] School of Human Movement and Nutrition Sciences, University of Queensland, Australia

[b] Institute of Sport, Exercise & Active Living (ISEAL), Victoria University, Melbourne, Australia

[c] Centre for Sport and Exercise Science Research, Edith Cowan University, Perth, Australia

[d] Brisbane Broncos Rugby League Football Club, Queensland, Australia

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Corresponding Author: Mr. Lachlan P. James, l.james1@uq.edu.au

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Abstract

Objectives: To determine those performance indicators that have the greatest influence on classifying outcome at the elite level of mixed martial arts (MMA). A secondary objective was to establish the efficacy of decision tree analysis in explaining the characteristics of victory when compared to alternate statistical methods.

Design: Cross-sectional observational.

Methods: Eleven raw performance indicators from male Ultimate Fighting Championship bouts (n=234) from July 2014–December 2014 were screened for analysis. Each raw performance indicator was also converted to a rate-dependent measure to be scaled to fight duration. Further, three additional performance indicators were calculated from the dataset and included in the analysis. Cohen's d effect sizes were employed to determine the magnitude of the differences between Wins and Losses, while decision tree (chi-square automatic interaction detector (CHAID)) and discriminant function analyses (DFA) were used to classify outcome (Win and Loss).

Results: Effect size comparisons revealed differences between Wins and Losses across a number of performance indicators. Decision tree (raw: 71.8%; rate-scaled: 76.3%) and DFA (raw: 71.4%; rate-scaled 71.2%) achieved similar classification accuracies. Grappling and accuracy performance indicators were the most influential in explaining outcome. The decision tree models also revealed multiple combinations of performance indicators leading to victory.

Conclusions: The decision tree analyses suggest that grappling activity and technique accuracy are of particular importance in achieving victory in elite-level MMA competition. The DFA results supported the importance of these performance indicators. Decision tree induction represents an intuitive and slightly more accurate approach to explaining bout outcome in this sport when compared to DFA.

Keywords

Combat sports, performance analysis, decision tree, athletic performance, discriminant function analysis

Introduction

Distinguishing the trainable characteristics of superior performance in a given sport can provide valuable insight for coaching and training practices. For instance, interventions can be designed to target those skills and attributes which have the greatest impact on competition success[1, 2]. Although the process of performance analysis can be undertaken from a biomechanical and physiological perspective, notational approaches employ an analysis of action variables related to a technical aspect of competition success [3]. Identifying combinations of those performance indicators that are most associated with outcome can be used to direct training towards more influential techniques while also formulating strategic game-plans for competition [4, 5]. Additionally, this information can provide a framework by which informed, within-competition coaching decisions can be made in response to certain patterns of action or opposition behaviour [1, 6]. The benefits of this information further extends to strength and conditioning practices, whereby once the decisive skills are clearly established, training interventions can then emphasise the development of the physiological mechanisms that underpin these manoeuvres[2]. Such analyses therefore play a pivotal role in the optimisation of the training process [4, 7].

Probabilistic statistical methods have been used to examine the interaction between performance indicators and competition outcomes in a number of sports, including Australian rules football [1, 8], rugby sevens [9], wrestling [10], and football [4]. However to the authors' knowledge, there has been no such inquiry into mixed martial arts (MMA) to date. This represents a notable gap in the scientific literature considering the marked growth in professionalism and the highly technical nature of this sport. Expressed as intermittent collision activity[11, 12], MMA combat is driven by techniques from more traditional combat disciplines in addition to its own specialised skills[13]. These foundational sports can be divided into the distinct categories of grappling and striking based upon their predominant techniques. Manoeuvres including throws, joint locks and chokes define grappling sports including judo, wrestling and Brazilian jiu-jitsu. In contrast, the striking combat which characterises boxing, kickboxing and karate is driven primarily by attacks such as punches and kicks[14]. The use of both modes of activity distinguishes MMA from other combat sports and results in the potential for a broad and highly complex series of events across both forms of combat to occur in order to achieve victory. An outcome may be rendered via judges' decision at the end of the scheduled duration based upon optimal execution of these strategies. Additionally, it is possible for an outcome to be reached prior to this in the event of a knockout, official stoppage or if a competitor signals that they are unable to continue. Therefore, competition can be completed in a matter of seconds or continue for the full scheduled time period, which is generally 15 to 25 minutes, across three to five rounds respectively at the elite level [15].

Some inquiry has been made into the technical factors of MMA activity at both the elite [11, 13] and lower-level [12]. Notably, Miarka et al. [13] compared performance indicators between winners and losers across a sample of professional bouts. Higher strike attempts and measures of positional advances during ground fighting were noted amongst winners. However, the inclusion criteria for this study excluded any fights that did not enter a third round, while the statistical procedures performed did not account for the influence or interaction of other indicators.

The primary aim of this study was to determine whether bout outcome at the highest level of MMA competition could be classified using commonly-reported performance indicators. A secondary objective sought to establish the efficacy of a non-linear modelling method when compared with a linear and univariate approach. Such findings could allow for evidence based coaching and training practices by contributing to a framework that guides attention and resources towards those skills that have the greatest impact on achieving victory.

Methods

The highest level of professional MMA competition takes place in the Ultimate Fighting Championship (UFC) [16]. As such, raw performance indicators from UFC competition were acquired upon formal request via Fightmetric (www.fightmetric.com); the official statistics and analytics provider to the organisation. Data from all male bouts from July 2014-December 2014 (n = 236) were screened for analysis. This period was chosen to provide a representative sample of contemporary

UFC competition over a time-frame narrow enough to ensure no major rule or tactical changes notably influenced results. This included 234 fights in which a winner was decided; a ‘no contest’ occurred in 2 bouts which were subsequently removed from the main analyses. The following 11 common performance indicators were extracted from the dataset, with terminology: total strikes attempted, total strikes landed, significant strikes landed, significant strikes attempted, significant distance strikes landed, significant distance strikes attempted, significant clinch strikes landed, significant ground strikes landed, takedowns attempted, takedowns landed and offensive passes. Following this, each raw performance indicator was converted to a rate-dependent measure to be scaled to fight duration. Additionally, successful (landed) overall strikes, takedowns and significant strikes were also expressed as a percentage of their respective attempts to produce three accuracy variables for inclusion in the analysis.

Descriptive statistics for winning competitors (represented as the mean difference relative to the opponent) for 13 performance indicators were obtained. Takedown accuracy was not included in the main descriptive and univariate analyses due to multiple missing values as a result of no takedown attempts being executed in a bout. This was to prevent the calculation of a misleading value that would bias the result against those competitors who successfully restricted their opponent from attempting a takedown. Cohen’s *d* effect sizes and their associated 95% confidence intervals were employed to determine the magnitude of the differences between Wins and Losses for each indicator in their rate-dependent and accuracy form. Strengths of the effect size differences were interpreted using the following categorisation system: <0.2 = trivial, 0.2-0.6 = small, 0.61-1.2 = moderate, and 1.2 – 2.0 = large[17].

Because of its ability to identify multiple combinations of factors that influence outcome, decision tree analysis was selected as the experimental model to classify MMA. This technique also has the advantage of being intuitive and easy to interpret by coaches and analysts [1, 6, 18], in addition to providing greater insight into the factors influencing an outcome variable than linear methods[19]. The decision tree analysis (chi-square automatic interaction detector (CHAID)) was used to classify outcome (Win and Loss) based on the 11 raw and three accuracy independent variables. To determine the efficacy of modelling rate-dependent indicators, a second decision tree was also constructing including only these adjusted (*n* = 11), and the same accuracy (*n* = 3), performance indicators. For both models, a minimum of 10 cases were required in order for a node to split, with a minimum gain ratio of 10% set for each variable with respect to model contribution[1]. A 10-fold cross validation was undertaken for both models, with classification accuracy reported as mean ± SD across all folds[20]. These measures were implemented with the intention of producing the most generalisable model. The 95% confidence limits relating to the classification accuracy of each model were also outputted. Two discriminant function analyses (DFA) were employed using both the rate-scaled and non-rate scaled performance indicators to allow comparison with decision tree induction. Validation of discriminant models was conducted using the leave-one-out method of cross-validation. Effect sizes were calculated in Microsoft Excel 2013 (Microsoft Corporation, Washington, USA), while all other analyses were conducted using SPSS for Windows Version 23.0 (IBM Corporation, Somers, New York, USA).

Results

Results from the main effect size comparisons revealed differences between Wins and Losses for the majority of performance indicators (Figure 1). Specifically, total strikes landed per minute, total strikes attempted per minute, significant strikes landed per minute, significant strike accuracy, significant ground strikes landed per minute and offensive passes all showed moderate differences for Wins and Losses. Only three variables did not show a small effect or greater, while no large effects were present. A moderate difference was present between Wins (*n* = 164) and Losses (*n* = 132) for the removed performance indicator (takedown accuracy: Win = 50.89 ± 32.47%, Loss = 28.96 ± 34.71%; Cohen's *d* = 0.62, 95% confidence interval = -3.88 to 5.13).

Figure 2 represents results relating to the first decision tree analysis using the raw and accuracy performance indicators. This model successfully classified bout outcome at 71.8% ± 3.6% across all folds (95% CI = 71.5 to 72.1%), including a sensitivity and specificity of 88.9% and 54.7%

respectively. Primarily influencing the classification of the model was significant ground strikes landed, while takedown accuracy and significant strike accuracy also contributed. For instance, 80.4% of fighters that recorded greater than four significant ground strikes landed per bout, went on to win the fight (Node 3, 111 out of 138 occasions). This victory rate was increased to 84.9% (Node 7, 101 out of 119 occasions) when these individuals also recorded a takedown accuracy of greater than 25%. The second decision tree model achieved a classification accuracy of 76.3% ± 5.1% across all folds (Figure 3) (95% CI = 75.8-76.8%) with a sensitivity and specificity of 73.5% and 79.1% respectively. Major performance indicators in the model included significant ground strikes landed per minute, strikes landed per minute, takedown accuracy and significant strike accuracy, with higher values recorded in each associated with Wins. For example, when a competitor lands greater than 0.850 significant grounds strikes per minute, he achieves victory in 91.5% of instances (Node 3, 86 out of 94 occasions). The likelihood of achieving a Win further increases to 96.3% when these fighters also deliver greater than 4.190 strikes landed per minute (Node 9, 79 of 82 instances).

The DFA achieved a classification accuracy of 71.4% (sensitivity: 75.6%, specificity: 67.1%, 70.1% cross-validation) and 71.2% (sensitivity: 76.1%, specificity: 66.2%, 69.4% cross-validation) for raw and rate-scaled indicators, respectively. For the first model, similar to the first decision tree analysis, significant ground strikes landed and takedown accuracy were important to explaining outcome, with offensive passes contributing strongly as well. Also similarly to the second decision tree model, significant ground strikes landed per min and takedown accuracy represented the most important performance indicators in classifying outcome in the second DFA, with offensive passes per minute also discriminatory.

**** Place Figure 1 about here ****

**** Place Figure 2 about here ****

**** Place Figure 3 about here ****

Discussion

The primary aim of this investigation was to determine whether outcome at the highest level of MMA competition could be classified using commonly collected performance indicators. The decision tree analyses identified multiple combinations of performance indicators that contribute to explaining bout outcome using both raw and rate-dependent indicators, with the latter revealing a higher classification accuracy. Impacting this finding was a relatively limited ability for Model 1 to accurately explain a Loss. This low level of specificity in concert with increased sensitivity suggest that the contribution of the raw performance indicators to achieving a Win was over-estimated. The improved classification rate, in particular its ability to detect a Loss, using the adjusted values is unsurprising as it corrects for the duration of each individual bout. This suggests that indicators in this form are superior when analysing data sets for relationships to outcome in such sports. It is of note that while the univariate comparisons identified all but two variables as having a non-trivial magnitude of effect, both decision tree models achieved its degree of accuracy despite including only 3 to 4 performance indicators. Furthermore, unlike isolated comparisons, this analysis technique revealed multiple combinations of performance indicators that contribute to victory thereby allowing for greater function in an applied setting. Accordingly, due to the multiple profiles that exist, the descriptive measures display a substantial amount of variance. Thus it is clear that not all victorious fighters consistently express these collective differences from their opponent in a given bout.

When compared to DFA, the decision tree method was slightly more successful at classifying outcome, and revealed multiple performance indicator profiles leading to victory. This suggests that decision tree analysis is a superior method for explaining the characteristics of performance in this sport. Previous reports have noted similar accuracy between linear (82.5%) and decision tree (81.5%) models in Australian football [1]. The differences between the two methods in this study can be explained by the multiple ways of achieving victory in MMA, which are better classified using a non-linear approach.

The first level of partitioning in both models clearly highlights the decisive nature of landing powerful strikes during ground fighting. When examining this technique, fundamental biomechanical principles in addition to observation of the sport suggests that unlike standing combat, the ability to throw a damaging strike during ground activity is almost entirely dependent on achieving an advantageous position on top of an opponent, and therefore may be somewhat less influenced by the technique of the strike itself when compared to this attack performed in a standing position. From an operational perspective this provides evidence that superior grappling ability may heavily impact victory in many cases. The influential nature of this mode of combat is reinforced in other pathways of both decision trees. In particular, the interaction between significant ground strikes landed per minute and takedown accuracy in nodes 1 and 5 in model 2 (Figure 3) highlights that the disadvantage suffered from landing no significant ground strikes per minute can be overcome by a takedown accuracy of >25%, which shifts the likelihood of winning into the athlete's favour. In further support of this is the finding that two of the three indicators included in Model 1 are representative of grappling activity. However, it is important to consider that although these results hold great applied value, it does not necessarily explain how a desirable position was attained. For example, scenarios may occur in which effective distance striking creates enough damage that a dominant ground fighting position can then be easily secured and retained. Regardless, based upon the analysis undertaken it is still reasonable to infer that grappling combat is particularly influential. This information should therefore be considered within the context of an individual athlete's strength and weaknesses when determining training allocations.

In addition to identifying the technical characteristics that influence outcome, these findings can also provide insight into the physiological qualities that may distinguish more successful competitors within the sport. Specifically, greater levels of maximal lower body strength and power have been reported in higher versus lower-tier competitors in the grappling sports of judo and wrestling [14]. Although differences exist between these sports and MMA that would drive a more aerobic adaptation[14], these findings indicate that lower body strength and power qualities are crucial to grappling performance and, therefore, might also be of notable importance to MMA success.

The decision tree partitioning also reveals the highly technical nature of MMA activity across both modes of combat. In particular, the accuracy of strikes and takedowns, in addition to strikes landed per minute, which are representative of successfully executed techniques, were featured in the model. This is in contrast to attempted, but not necessarily successful strikes, significant strikes and takedowns, which did not meaningfully impact the result. Such findings are in contrast to the magnitude based comparison which determined total strikes attempted per minute as possessing the second highest magnitude of effect of all 13 variables. Furthermore, these models are in distinct from previous findings that report attack attempts as a key factor in achieving victory in MMA and consequently make training recommendations based upon this [13]. This provides further evidence that isolated comparisons have the potential to provide misleading results [1], particularly within complex and dynamic sports such as MMA.

To this end, the findings of this present study suggest that it is the accuracy of a manoeuvre, rather than the volume executed, that is of greatest importance in determining a winning outcome. Alongside increasing the likelihood of victory, training strategies that consider this would also have the desirable effect of potentially reducing the physical stress on the athlete, resulting in lowered opportunities for injury, increased recovery and the strategic reprioritisation of alternate training tasks (conditioning, strength and power development and tactics) based on the principles of periodisation [25] [26] and the individual athlete's window of adaptation[27].

Conclusions

The findings of this current study reveal multiple combinations of actions that explain winning at the highest level of MMA competition via decision tree analysis. Amongst non-rate dependent indicators, significant ground strikes landed, takedown accuracy and significant strike accuracy classified the first model. Similarly, when rate-dependent indicators were analysed, significant ground strikes landed per minute, takedown accuracy, strikes landed per minute and significant strike accuracy were featured. The DFA analysis supported the relevance of these performance indicators to classifying outcome. This highlights both the influential nature of grappling combat and demand for technical precision across both striking and grappling. The information presented here is of great practical value to coaches of the technical, tactical and physiological components of the sport.

Practical implications

- Victory at the elite level of MMA competition is impacted by the accuracy of the technique, while executing an increased volume of attempts does not contribute to a winning result.
- In preparation for competition sports specific coaches can use these findings to emphasise those techniques and strategies most likely to determine victory.
- The numerous performance indicator combinations identified can provide informed guidance for the diverse and unique situations that an athlete encounters during competition.
- From a physiological perspective these results can be considered by strength and conditioning coaches to ensure training plans are effectively designed to develop the mechanisms underpinning the predominant and influential actions.

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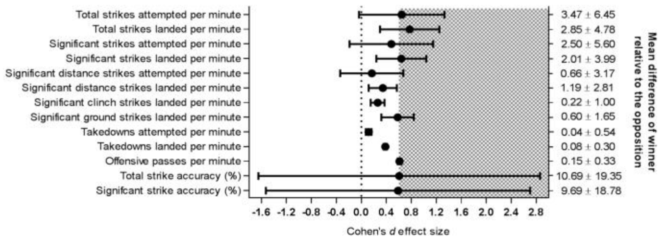
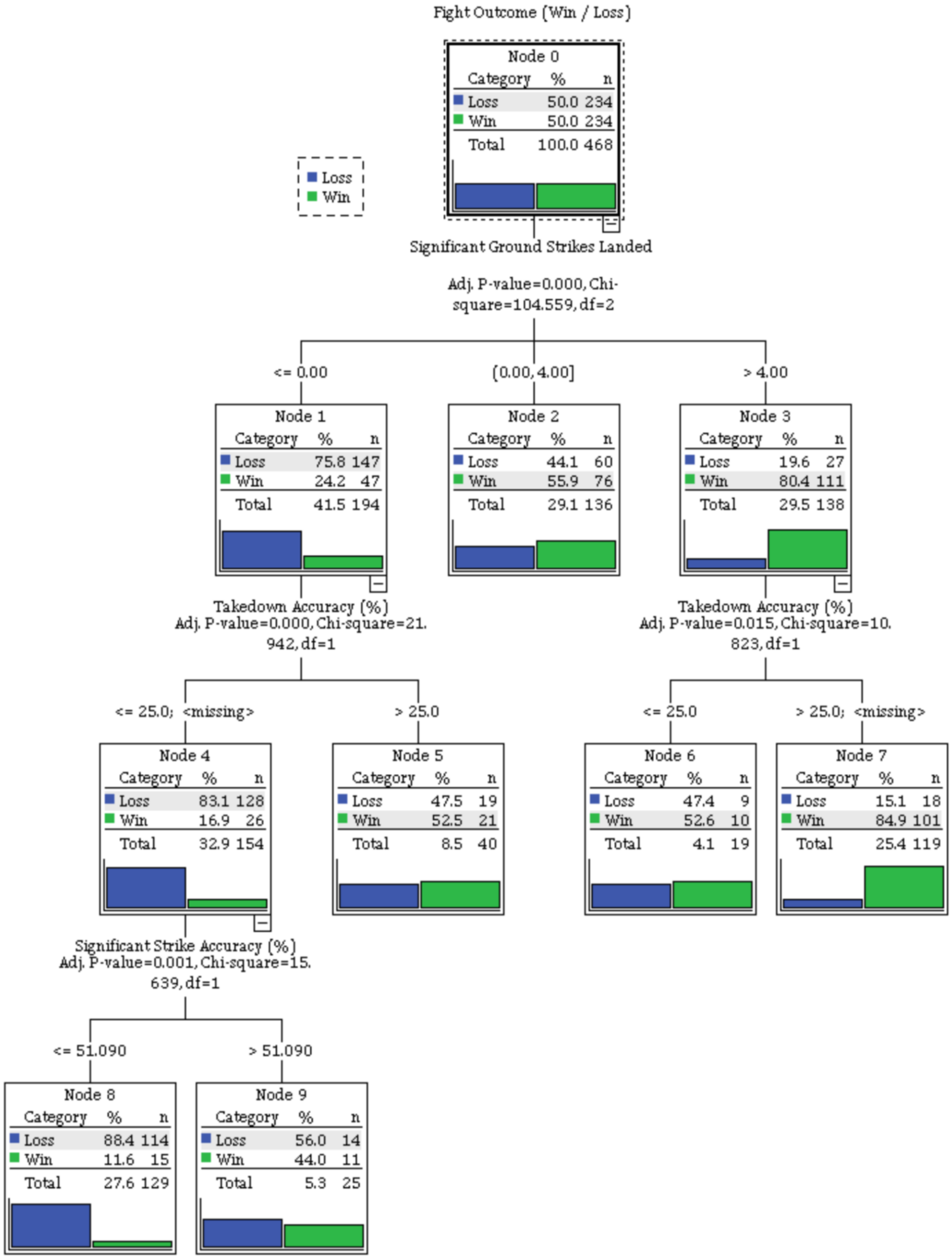
Figure Legends

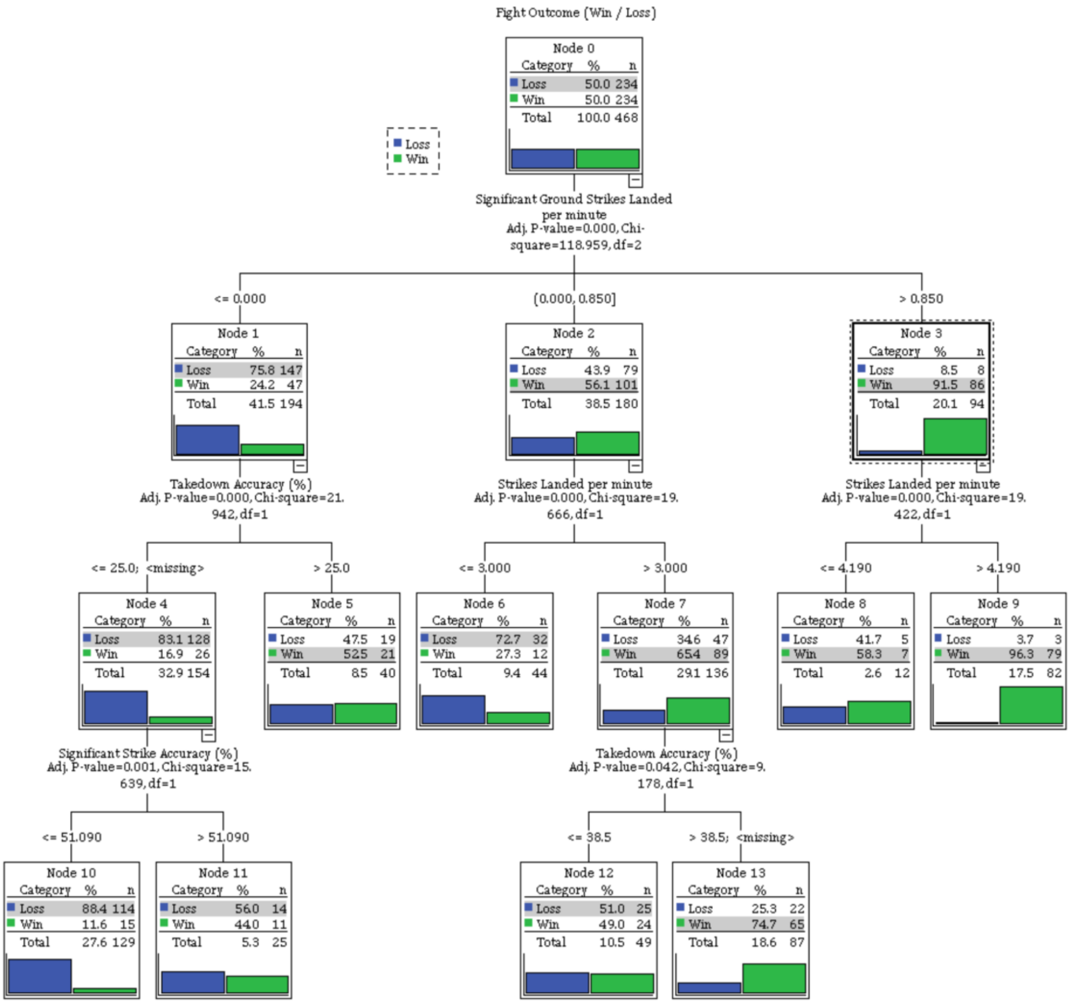
Figure 1. Effect size calculations (±95% confidence intervals) and descriptive statistics of rate dependent and accuracy based performance indicators. A positive effect represents a higher value by the bout winner. The shaded area indicates a moderate to large effect.

Figure 2. Model 1. Decision tree analysis of non-rate dependent and accuracy performance indicators. Node 0 includes the Win and Loss result for all 234 bouts. The first level below this describes the impact of the most influential performance indicator on outcome, in this case it is significant ground strikes landed. The algorithm partitioned the count frequency of this indicator into three categories, and describes its influence on outcome within each node. The model continues to split in this fashion until classification accuracy is no longer markedly improved.

Figure 3: Model 2. Decision tree analysis of rate-dependent and accuracy performance indicators. Node 0 includes the Win and Loss result for all 234 bouts. The first level below this describes the impact of the most influential performance indicator on outcome, in this case it is significant ground strikes landed per minute. The algorithm partitioned the rate of this indicator into three categories, and describes its influence on outcome within each node. The model continues to split in this fashion until classification accuracy is no longer markedly improved.


Total strikes attempted per minute
Total strikes landed per minute
Significant strikes attempted per minute
Significant strikes landed per minute
Significant distance strikes attempted per minute
Significant distance strikes landed per minute
Significant clinch strikes landed per minute
Significant ground strikes landed per minute
Takedowns attempted per minute
Takedowns landed per minute
Offensive passes per minute
Total strike accuracy (%)
Signifcant strike accuracy (%)
3.47 ± 6.45
2.85 ± 4.78
2.50 ± 5.60
2.01 ± 3.99
0.66 ± 3.17
1.19 ± 2.81
0.22 ± 1.00
0.60 ± 1.65
0.04 ± 0.54
0.08 ± 0.30
0.15 ± 0.33
10.69 ± 19.35
9.69 ± 18.78
-1.6 -1.2 -0.8 -0.4 0.0 0.4 0.8 1.2 1.6 2.0 2.4 2.8
Cohen's d effect size
Mean difference of winner relative to the opposition


Fight Outcome (Win / Loss)
Node 0
Category % n
Loss 50.0 234
Win 50.0 234
Total 100.0 468
Loss
Win
Significant Ground Strikes Landed
Adj. P-value=0.000, Chi-square=104.559, df=2
<= 0.00
(0.00, 4.00]
> 4.00
Node 1
Category % n
Loss 75.8 147
Win 24.2 47
Total 41.5 194
Node 2
Category % n
Loss 44.1 60
Win 55.9 76
Total 29.1 136
Node 3
Category % n
Loss 19.6 27
Win 80.4 111
Total 29.5 138
Takedown Accuracy (%)
Adj. P-value=0.000, Chi-square=21.942, df=1
Takedown Accuracy (%)
Adj. P-value=0.015, Chi-square=10.823, df=1
<= 25.0; <missing>
> 25.0
<= 25.0
> 25.0; <missing>
Node 4
Category % n
Loss 83.1 128
Win 16.9 26
Total 32.9 154
Node 5
Category % n
Loss 47.5 19
Win 52.5 21
Total 8.5 40
Node 6
Category % n
Loss 47.4 9
Win 52.6 10
Total 4.1 19
Node 7
Category % n
Loss 15.1 18
Win 84.9 101
Total 25.4 119
Significant Strike Accuracy (%)
Adj. P-value=0.001, Chi-square=15.639, df=1
<= 51.090
> 51.090
Node 8
Category % n
Loss 88.4 114
Win 11.6 15
Total 27.6 129
Node 9
Category % n
Loss 56.0 14
Win 44.0 11
Total 5.3 25



Fight Outcome (Win / Loss)
Node 0
Category % n
Loss 50.0 234
Win 50.0 234
Total 100.0 468
Loss
Win
Significant Ground Strikes Landed per minute
Adj. P-value=0.000, Chi-square=118.959, df=2
<= 0.000
(0.000, 0.850]
> 0.850
Node 1
Category % n
Loss 75.8 147
Win 24.2 47
Total 41.5 194
Node 2
Category % n
Loss 43.9 79
Win 56.1 101
Total 38.5 180
Node 3
Category % n
Loss 8.5 8
Win 91.5 86
Total 20.1 94
Takedown Accuracy (%)
Adj. P-value=0.000, Chi-square=21.942, df=1
Strikes Landed per minute
Adj. P-value=0.000, Chi-square=19.666, df=1
Strikes Landed per minute
Adj. P-value=0.000, Chi-square=19.422, df=1
<= 25.0; <missing>
> 25.0
<= 3.000
> 3.000
<= 4.190
> 4.190
Node 4
Category % n
Loss 83.1 128
Win 16.9 26
Total 32.9 154
Node 5
Category % n
Loss 47.5 19
Win 52.5 21
Total 8.5 40
Node 6
Category % n
Loss 72.7 32
Win 27.3 12
Total 9.4 44
Node 7
Category % n
Loss 34.6 47
Win 65.4 89
Total 29.1 136
Node 8
Category % n
Loss 41.7 5
Win 58.3 7
Total 2.6 12
Node 9
Category % n
Loss 3.7 3
Win 96.3 79
Total 17.5 82
Significant Strike Accuracy (%)
Adj. P-value=0.001, Chi-square=15.639, df=1
Takedown Accuracy (%)
Adj. P-value=0.042, Chi-square=9.178, df=1
<= 51.090
> 51.090
<= 38.5
> 38.5; <missing>
Node 10
Category % n
Loss 88.4 114
Win 11.6 15
Total 27.6 129
Node 11
Category % n
Loss 56.0 14
Win 44.0 11
Total 5.3 25
Node 12
Category % n
Loss 51.0 25
Win 49.0 24
Total 10.5 49
Node 13
Category % n
Loss 25.3 22
Win 74.7 65
Total 18.6 87