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Movement strategies in elite amateur boxing

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Movement strategies in elite amateur boxing.

A thesis submitted to Middlesex University in partial fulfilment of the requirements
for the degree of Master of Science (by Research)

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Abstract

Activity profiling of boxing based on the number and type of punches thrown has been examined on several occasions. To better understand the activity profile of two successful elite amateur boxers, 100 rounds of sparring and international competition were analysed. A bespoke computer vision player tracker was developed to objectively assess movement strategies of boxers. Sparring in training and competition requires ~ 19 punches per minute. The two boxers analysed exhibit clearly differing styles. Front-foot boxers spend more time in the centre of the ring, and back-foot boxers spend comparatively less time in the centre and more time around the edges. Successful boxers have a higher work rate when they occupy the space closest to the centre of the ring. Compared to their opponents, the front-foot boxer had a higher activity level when furthest from the centre of the ring and the back-foot boxer had a lower activity level. The ratio of successful punches to total punches thrown does not increase with round duration. The number of punches thrown, and distance covered in the last minute of a round was equivalent or increased compared to the first minute. Further assessment of the different boxing styles and their interactions in the context of competition outcome is needed.

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2. Introduction

Boxing has been an Olympic sport since 1904 and has featured at every Games since 1920, with women competing since 2012. In a competitive amateur boxing bout, there are five judges situated around the ring. A winner is decided by the judges based upon three factors; firstly, the number of quality blows in the target area (where the target area is the front and side of the head, or torso above the waist); secondly, domination of the round by technical and tactical superiority; the final factor for judges to consider is “competitiveness” (The International Boxing Association, 2020).

Clearly, given the information available to a judge during a bout, the second and third factors that must be included are subjective, whereas the first is a more objective measure. The previous scoring system for boxing (for amateur fights before 2013) used the number of punches landed as the scoring method (Davis et al., 2017). This was changed to allow the judges to give credit to boxers beyond just landing punches. To maximise their chance of success in competition, athletes train to ensure they can meet the anticipated demands of a contest. Previous research has primarily focussed on the number and type of punches thrown by boxers with respect to bout outcome, and some provided suggestions for which tactical elements to focus on during training.

A boxer may be broadly classified as a front-foot or back-foot boxer. A front-foot boxer would likely throw a high number of punches and seek to control the centre of the ring, whereas a back-foot boxer would be more comfortable keeping a distance from their opponent and only entering attacking range to land punches. For this approach to be successful, the back-foot boxer must achieve high-quality scoring punches. Analysis of a boxer’s strengths and weaknesses, and knowledge of their

boxing characteristics (stance, style etc.), and comparison to the respective features of their next opponent are used to prepare for a bout (O'Donoghue & Mayes, 2013). A more complete understanding of different boxers and different boxing styles would benefit from objective detail on a boxer's movements and positioning relative to their opponent. Computer vision can be used to automatically detect and track objects in image sequences, producing positional information for both boxers involved in a bout in significantly less time than an analyst manually producing the same data. Improved knowledge of the movement demands could also inform a boxer's physical training and contribute to understanding of the different boxing styles.

The aim of this study was to establish a tracking system and then use the system to analyse the activity profile of two highly successful elite amateur boxers in comparison to each other and their opponents.

3. Literature Review:

A boxer's tactical preparation is underpinned by an understanding of the relative strengths and weaknesses of themselves and their next opponent. Commonly, video footage is utilised to aid tactical and psychological preparation for a bout. Previous research has focussed on the need to prepare an athlete to meet the required physical demands likely to lead to a successful outcome. Primarily this research has looked to quantify type and number of punches thrown by successful and unsuccessful boxers. A more complete understanding of different boxers and different boxing styles would benefit from objective detail on a boxer's movements and positioning relative to their opponent.

Davis et al. found that boxing at the elite level require male boxers to maintain an activity rate of ~20 punches per minute over a three-minute round (Davis et al.,

2015). Thomas found that elite female boxers threw ~20 punches per minute (over a two-minute round), with winners having higher punch efficiency than losers (Thomas, 2015). Davis et al. later established that male amateur boxers needed to be able to maintain ~21 punches per minute (over a three-minute round), with a strategic target to increase punch efficiency as a fight progressed (Davis et al., 2018). Objective definitions of the different styles of boxer are not currently available, and the two boxers that face each other in a fight will influence the technical demands of that fight (Thomson & Lamb, 2016).

The activity level during a fight has been found to decrease with increased fight duration (Thomas, 2015). As a fight progresses, the heart rate (Slimani et al., 2018) and blood lactate (Davis et al., 2013) of a boxer increases, but this cannot continue to increase indefinitely. A boxer that was able to maintain or increase their work rate in the latter stages of a fight might gain an advantage over their opponent.

The areas of the ring that boxers occupy during a fight can restrict their ability to move away from an opponent. The position with most freedom to move to avoid an opponent's attack is the centre of the ring. One way to measure which boxer is controlling the centre of the ring is to look at which boxer is closest to the middle. A front-foot boxer would expect a high proportion of their time to be spent close to the centre of the ring, and a back-foot boxer would expect the opposite. The activity profile of a boxer in different areas of the ring, and in different positions relative to their opponent has not been established.

Achieving an activity rate of around 20 punches per minute is not sufficient to win a fight. The punches must land in the target area on the opponent. In competitions the judges' decision did not reflect the number of punches landed in three of sixteen boxing fights (Davis et al., 2013). The "ten-point must" scoring system has been

found to be subjective and based on more than the number of punches thrown or landed (Dunn et al., 2017). Whilst a boxer can make defensive actions such as a block, which might cause a punch to land on their arms or gloves, they are also able to move to a position outside of punching range of the other boxer. By occupying a space beyond the reach of their opponent, a boxer can effectively minimise the number of scoring blows achieved by their opponent (Davis, et al., 2016). Ideally a boxer would be able to maintain a close enough distance to strike their opponent, but far enough away that it would be possible to react to, and avoid, their offensive movements (Tabben et al., 2015). The amount of time spent within punching range must be managed by the boxer to maximise scoring opportunities.

Currently training and competition are recorded by performance analysts to aid feedback to the coach and athlete. Video has been shown to improve feedback and learning rate of people acquiring a skill (Aiken et al. 2012). The video is used immediately after the training session has ended, or in a later review session.

Positional tracking is not currently employed in boxing, or other combat sports.

Several other sports do use player tracking technology to better understand patterns of play and successful strategies (Bourbousson, et al., 2010; Thomas et al., 2017).

Many sports that utilise player tracking technology generate positional data from a combination of sensors worn by the players and computer vision systems (Rhodes et al., 2014). The most developed systems use the computer vision systems to extract detail from video footage that cannot be generated by wearable sensors alone (Noceti et al. 2011). The computer vision systems used allow for automated data production, which leads to larger data sets from which to generate performance enhancing insight.

Exclusively computer vision based tracking has been used in other indoor sports (Perš et al. 2001; Wu et al., 2019), but not yet in boxing using simple single camera systems. Perš et al. used overhead cameras to track two players in squash using a computationally inexpensive background removal system. Squash also has the possibility that the two players may appear to collide and thus present only on foreground object. Perš et al. utilised the previous positions of both players to separate a foreground blob in this case.

The primary issue that developers of computer vision systems for sports applications face is definition and description of the environment. Sports take place in a wide variety of locations, and each presents unique challenges. Sports can take place inside or outside, with or without crowds or advertising hoardings, and with or without clearly delineated areas of play. The video footage of the sport may be from permanently fixed cameras, fixed locations that can pan, tilt, or zoom, or freely moving locations. Each of those factors would change the approach taken in applying a computer vision system. Often the general location information for a sport is consistent, but specific details will change. Given the variety of requirements, it may be prudent to have a bespoke system for different sporting environments.

The number of players in a game adds further demands to a player tracking system. Aside from the need to track multiple objects, there is a higher likelihood of occlusion, and sports requiring larger areas of play often take place outside, meaning that illumination changes must be accounted for (Manafifard et al. 2017). In sports such as boxing, there is a clear occlusion problem caused by the ropes that define the playing area if the camera is positioned to the side of the ring. Boxing requires at least two participants, with the possibility of also having a referee.

The functional architecture used for object tracking is described by Jalal and Singh as three interacting modules: object modelling including features and representations, foreground segmentation with background modelling and subtraction, and finally object tracking (Jalal & Singh 2012). Approaches for automated motion tracking have been used successfully in domains outside of sports performance, notably for surveillance but this is achievable because identification of objects is not necessary (Barris & Button, 2008). Reliable automated motion tracking relies on a robust set of identifiers that can be used to classify individual players (Monier et al. 2009). In competition the colours worn by each boxer are specified according to tournament rules, and in the training environment it is possible to allocate differently coloured clothing to opposing boxers.

Often the availability of adequate video and computational facilities in sports venues has hampered the application of automated tracking technology to sport (Barris & Button, 2008). In the video footage used in this study, the camera position above the ring means that occlusion from the ring ropes was not an issue. Overhead time of flight cameras have been utilised to categorize punch types in boxing (Kasiri-Bidhendi et al. 2015; Kasiri-Bidhendi et al. 2017), but time of flight cameras are not readily available in most boxing training gyms. A cheap, simple, monocular computer vision system represents the most practical solution for most boxing training environments.

As the provided camera position creates a need for the transformation (Vučković et al. 2010), an assessment of the error and reliability of the tracking system will be made. Establishing the foreground objects in the scene allows for classification of the objects as one boxer or the other. To generate useful data on each boxer, it is necessary to identify each boxer in some way. Computer vision tracking systems

using colour filters have been used to identify players from different teams in a game (Yang & Li, 2017). This information could be used to identify two boxers (and if necessary, a referee) within the boxing ring. Identifying the boxers with this method enables differentiation between boxers if they come close enough to one another that a foreground mask identifies both boxers as a single object. Establishing the respective colour properties of each boxer during video processing means the system can cope with the same boxer wearing different clothing on different training days. Referee masking can also be used where the referee's clothing colour is known in advance (Ivankovic, et al., 2014). Alternatively, the foreground objects can be labelled by the user and their positional data assigned to an athlete's name. Tracking two boxers in the boxing ring allows calculation of the distance between them and whether they are within punching range. Distance metrics are often used to quantify training (Akenhead et al., 2016). Starting a tournament or fight in optimal physical condition is the result of balancing the training load and stress (Allen et al, 2019).

4. Methods:

4.1 Sample

One hundred videos each representing one round of a fight split between competition and training footage. Each video involved one of two highly successful, elite amateur boxers that compete in the 75kg female (middleweight - MW) and 69kg male (welterweight - WW) divisions, respectively. Ethical approval for the study was provided by the sports science sub-committee of Middlesex University's ethics committee.

Thirty-eight rounds of WW's 13 competitive fights (178 ± 7.8 seconds) during 6 international competitions between June 2017 and June 2019. Two bouts were stopped by the referee before the completion of 3x3 minute rounds. Of the 13 fights, the boxer won 11 and lost 2.

Sixty-two rounds (169 ± 19.1 seconds) of male and female sparring during training between July 2018 and November 2020. Sparring sessions may not match the competition format – they may not be made up of 3x3 minute rounds between the same two boxers, and there is no referee present. The recordings, from a camera mounted above a boxing ring, provided an unobstructed view of all rounds which included fifteen opponents from the elite national training squad. The male and female boxers did not always train in the ring under the camera, therefore not every sparring session was available for retrospective analysis.

4.2 Definitions:

Every punch thrown by both boxers in each video was manually tagged according to four binary classifications, giving a total of 16 possible outcomes (**Appendix 3**).

Punch classifications used in this study were based on Thomson et al (2013). A punch was categorised as successful or unsuccessful depending on whether it visibly landed on the opponent's target area (successful) or missed the opponent's target area (unsuccessful). Defensive actions were not recorded. Success rate is the percentage of punches thrown that landed successfully. Activity level represents the total number of punches per minute (PPM) thrown by a boxer, and work rate describes the distance per minute.

The inside boxer is defined as the boxer closest to the centre of the ring at any given time, with the outside boxer being further from the centre of the ring. Attacking ranges are defined as according to one of three bands of distance between the boxers.

Less than 1m between the boxers is punching range, between 1m and 1.75m is attacking range, and 1.75m or more is out of range.

The basis for the defined zones were the visual aid lines painted onto the ring floor by the coaches. Zone 1 is the central circular zone, with a diameter of 2 metres, located at the centre of the ring. Zone 2 is the area between the outside of zone 1 and a concentric circle with a diameter of 4 metres. Zone 3 is the area between the outside of zone 2, and a square 0.5 metres inside the ropes. Zone 4 is the remaining area of the ring outside of zone 3 (Figure 1).

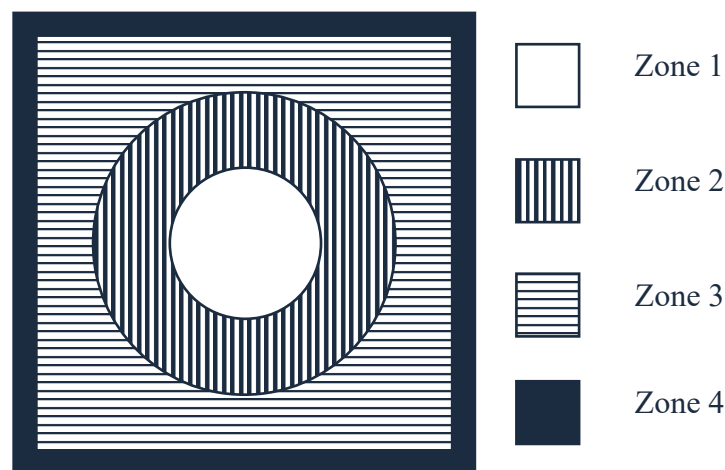


Figure 1: Definition of zones within a boxing ring.

4.3 Procedure:

The video footage for each round was processed using a multi-player tracker script, written for the purposes of this analysis, that has been implemented as a software solution for use by performance analysts (Figure 2). The script generated a background image by finding the mean values for each pixel over the first minute of the video. This mean frame image was then presented to the user, and the user selected the location of the corners of the ring. This step was necessary for adjusting the frame transformation if the relationship between the camera and the boxing ring

of interest changes. The videos were transformed so that only the area including the boxing ring was processed. For each frame of the video, the current frame was compared to the background image, and objects were defined as foreground if the difference in any of the three colour channels of the current frame was greater than a threshold value. The two largest foreground objects in the first frame of the video were taken to be the two boxers in the ring, and colour information for each boxer was stored to comparison to foreground objects and allocation of boxer details in future frames. The two foreground objects found in the first frame were presented to the user so that the correct name could be selected for each boxer. In video frames after the first frame, the objects were allocated as being a particular boxer based on proximity to their previous position. In the case that the boxers were touching and only one foreground object was visible, the foreground object was compared pixelwise to the colour information for each boxer, and each pixel was allocated to the boxer with a pixel value in each colour channel closest to the stored information. The location of each boxer was then calculated from the largest connected area after pixelwise colour comparison. The boxer's location in any frame was calculated as the centroid position of the respective foreground object. Positional information was exported for each boxer as a comma-separated-value (CSV) file once the processing had been completed, with a new line for each frame of the video. Whilst the tracker was processing the video, a new version of the video was saved with a frame number overlayed to facilitate accurate recording of the timing of punches thrown.

For each video, punches thrown by both boxers were manually tagged, and the information for type of punch thrown was added to the appropriate row, based on the frame number, of the CSV file.

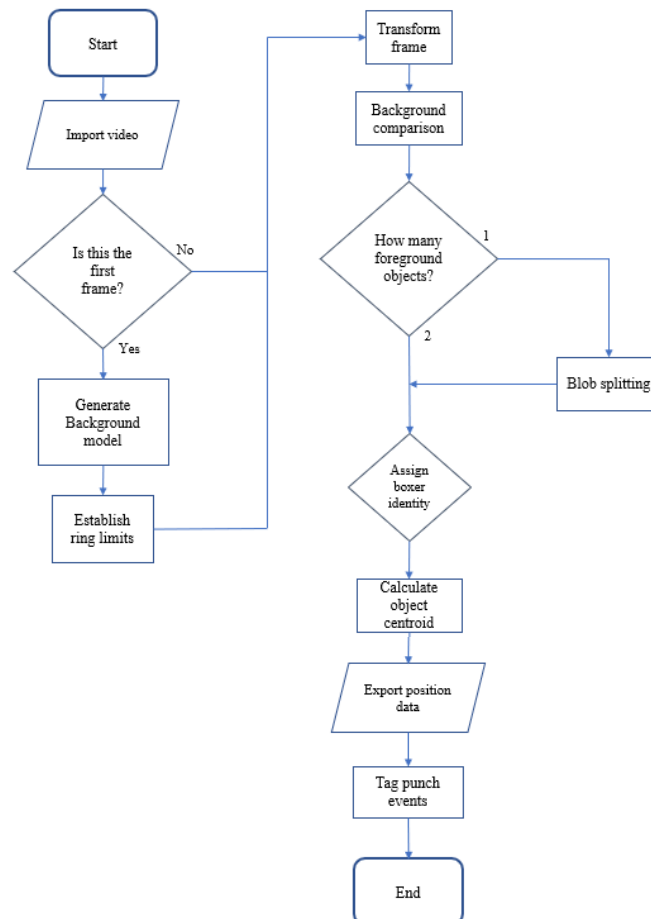


Figure 2: Bespoke player tracker process.

4.4 Reliability:

Competition video footage was tagged by the two performance analysts at GB Boxing (8- and 4-years' experience respectively), and inter-observer reliability was tested by both observers independently tagging the same bout. One observer manually tagged the punch events in the training video footage. The competition observers matched the punch classification on 215 of 235 punches. All punch events

apart from “lead uppercut” had Kappa statistics of greater than 0.8, suggesting almost perfect agreement. There was only one instance of a possible lead uppercut in the tagged bout. Intra-observer reliability was tested with the observer tagging the same training round three weeks apart. The level of agreement between the two observations was assessed via Cohen’s Kappa statistic (Cohen 1960; Landis & Koch, 1977; Robinson & O’Donoghue, 2007). The observer matched the punch classification on 159 of 161 punches. All punch events had Kappa statistics of greater than 0.8, suggesting almost perfect agreement (Table 1).

Table 1: Intra-observer reliability – Kappa values for punch types.

Punch Type	Kappa
SLHB	1.00
SLHH	0.96
SLSB	1.00
SLSH	0.99
SRHB	1.00
SRHH	1.00
SRSB	1.00
SRSH	1.00
ULHB	1.00
ULHH	0.97
ULSB	1.00
ULSH	0.98
URHB	1.00
URSB	1.00
Overall	0.98

The reliability of the player position determined by the script was evaluated using precision plots (Babenko et al., 2011; Wu et al., 2013). Five hundred frames from

four videos were selected randomly using the RANDBETWEEN function in Excel (Microsoft, version 2008) using the first and last frames in the video as the bounding values. The position of each boxer in the frames was manually annotated as the best estimation of the position of the base of the spine. This position was selected to give a more accurate position estimation than the boxer's head, as boxers often lean considerably away from a vertical position without moving. Each focus boxer was in two of the four videos selected. The precision plot shows the percentage of frames for which the estimated boxer location was within a given Euclidean pixel distance of the ground truth (Figure 3).

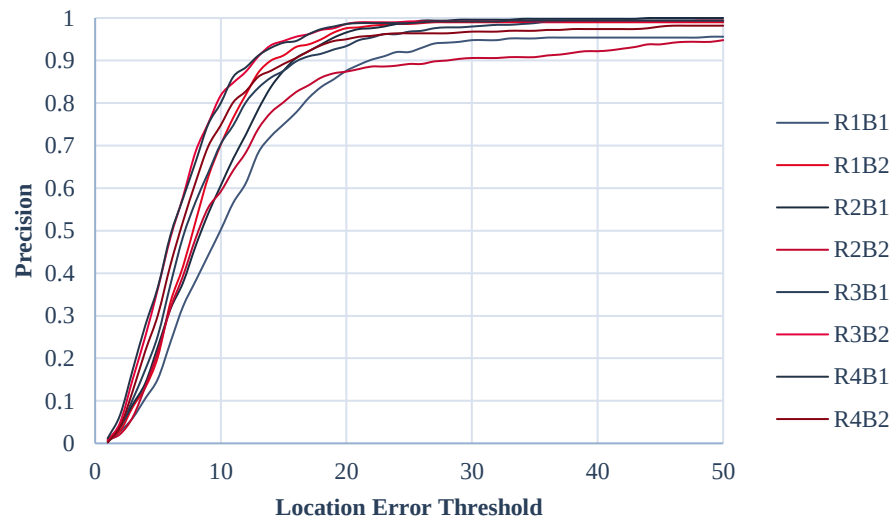


Figure 3: Precision plots for each boxer in each round of the reliability sample.

At a threshold of 20 pixels, mean precision of all eight boxers over the four sets of video frames was 94.35% (Table 2).

Table 2: Mean precision at different pixel threshold values.

Threshold (pixels)	10	20	30	40	50
Mean Precision	0.68	0.94	0.97	0.98	0.98

4.5 Statistical analysis:

Results were collated and statistical procedures were implemented using Excel (Microsoft, version 2008) and Minitab (Minitab®, version 18). Descriptive statistics for variables were calculated and are reported as mean $\pm$ standard deviation (95% confidence interval). A 2-sample t test was used to evaluate the difference between training and competition activity level, whether a focus boxer spent more time as the inside or outside boxer, and work rate as the inside or outside boxer. Time spent and activity level in each zone was assessed via a one-way ANOVA, with Tukey pairwise comparison. Effective punching range was tested using chi-square goodness of fit. A significance level of $p < 0.05$ was used for all tests.

5. Results:

WW (the male welterweight) and his opponents consistently threw 19 PPM in both competition (± 8.44) and training (± 4.31). There was not sufficient competition footage to make an informed assessment of MW's (the female middleweight) performance in competition to compare to training. The following results are based entirely on training data.

5.1 Punches, Movement, and Success

WW threw the same PPM as his opponents ($T = -0.32$, $DF = 61$, $p = 0.752$), whereas MW threw 14 ± 3.37 PPM, 6 fewer than her opponents ($T = -4.51$, $DF = 41$, $p < 0.001$). WW and his opponents both covered 70 ± 11.7 metres per minute ($T = 0.46$, $DF = 60$, $P = 0.648$), but MW 77 ± 21.8 covered metres per minute, 13 more than her opponents ($T = 2.74$, $DF = 50$, $p < 0.01$). WW landed 10% higher ratio of successful to unsuccessful punches (success rate) and MW had a 5% higher success rate than their opponents (WW: $T = -3.88$, $DF = 61$, $p < 0.001$, MW: $T = 1.71$, $DF = 54$, $p <$

0.05), however the increased success rate did not offset the lower number of punches thrown by MW and her 8 ± 2.43 successful PPM was 3 less than her opponent ($T = -2.66$, $DF = 38$, $p < 0.05$), while WW had 14 ± 4.03 successful PPM, 2 more than his opponents ($T = 2.39$, $DF = 61$, $p < 0.05$). Successful punch range was different for each boxer (Chi-square = 87.078, $DF = 5$, $p < 0.001$, Cramer's $V = 0.21$). WW's highest punch success percentage fell within the range 0.31m to 0.6m, with success ratio declining with increasing distance from the opponent (Figure 4).

MW's highest punch success percentage was at the greatest distance, but there were only 11 punches in that category. Success ratio in the three categories up to 0.9m were similar (64.8%, 65.1%, 64.2%), with success ratio declining with increasing distance from the opponent from 0.61m upwards until the final category (Figure 4).

5.2 Activity Level and Movement by Zone

WW spent most time in zone 1, and less time zones further from the centre of the ring ($F = 206.84$, $DF = 3$, $p < 0.001$). WW spent more time in zone 1 than MW ($T = 4.39$, $DF = 53$, $p < 0.001$), equivalent time in zone 2 ($T = 0.02$, $DF = 56$, $P = 0.985$), and MW spent more time in zones 3 ($T = -5.41$, $DF = 42$, $p < 0.001$) and 4 ($T = -3.92$, $DF = 34$, $p < 0.001$) (Figure 5). The clear difference in where the boxers spent their time during a round supports the hypothesis that different styles can be effective in boxing.

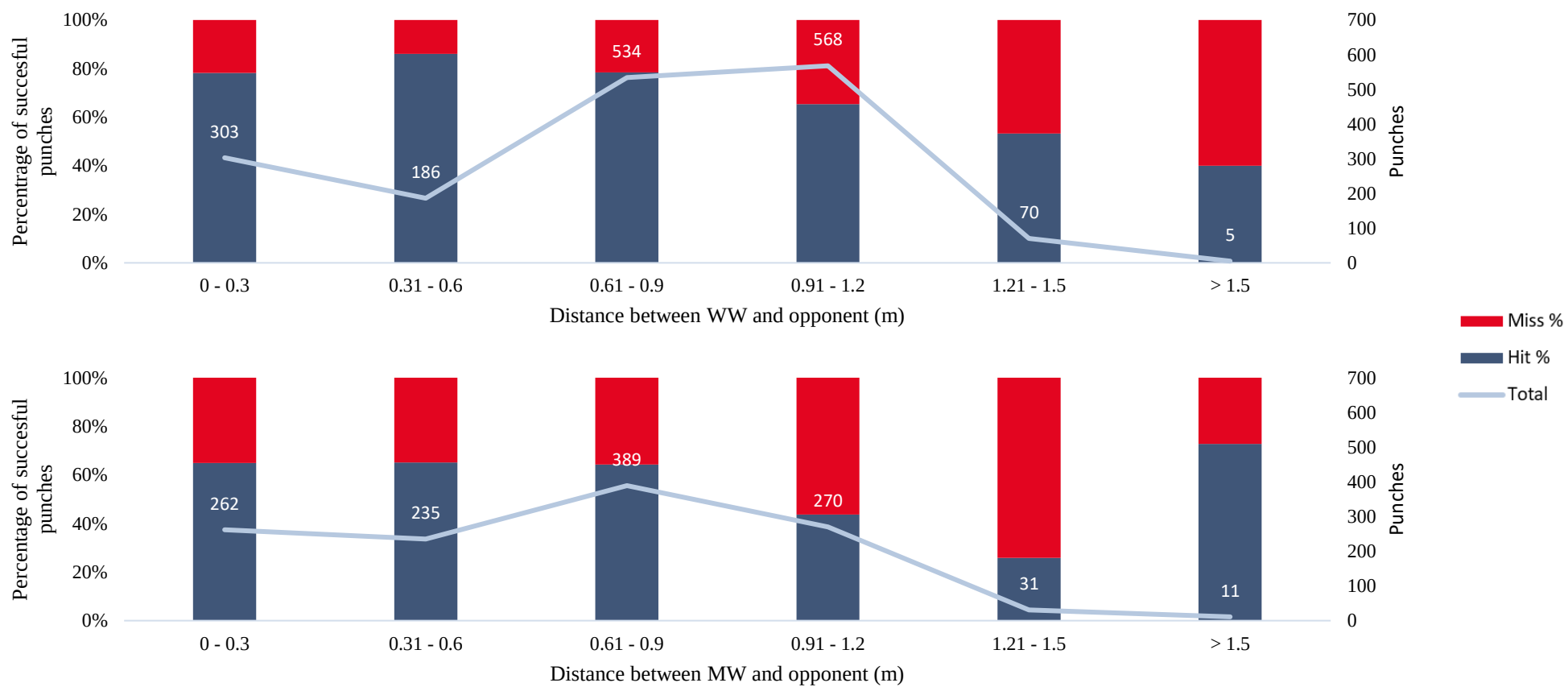


Figure 4: MW's and WW's successful and unsuccessful punches by distance between boxer

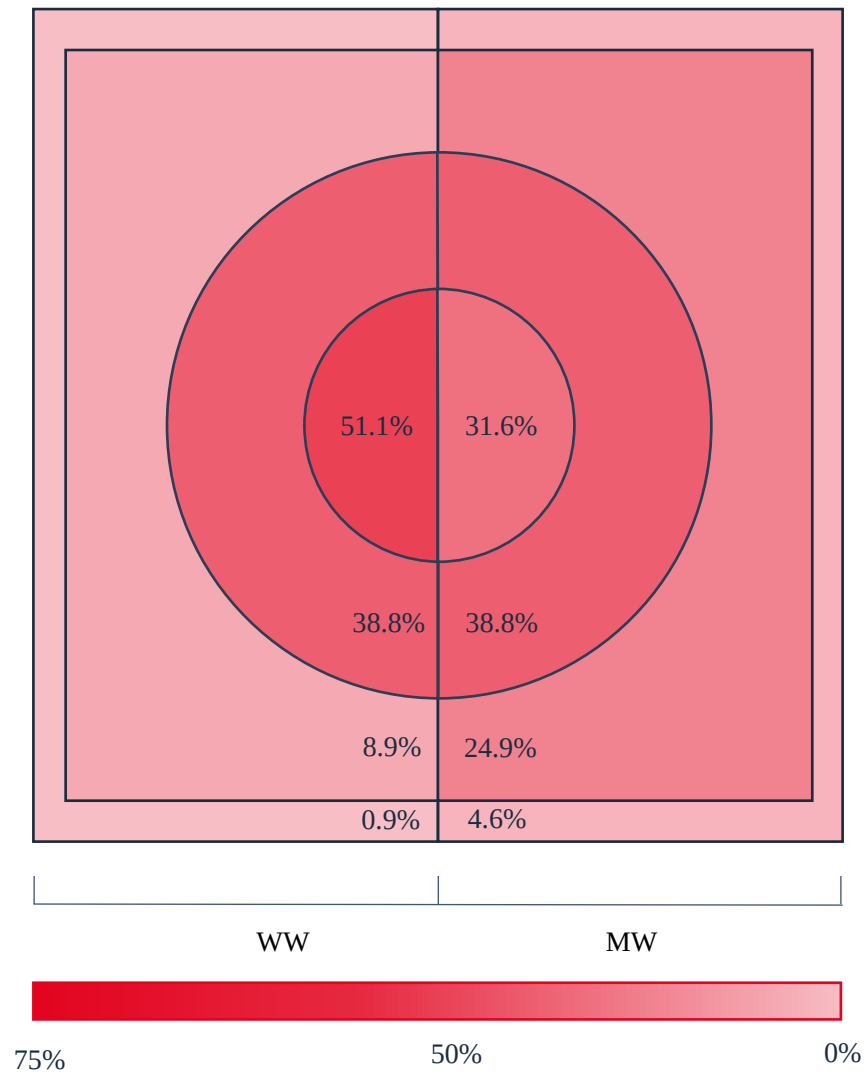


Figure 5: Time spent in each ring zone by each boxer.

WW's PPM was the same as his opponent in all four zones (Z1 $T = 0.67$, $DF = 58$, $p = 0.504$; Z2 $T = -0.36$, $DF = 60$, $p = 0.722$; Z3 $T = -0.63$, $DF = 43$, $p = 0.529$; Z4 $T = 1.01$, $DF = 60$, $p = 0.315$) and his PPM was lower in zone 4 than in zones 1, 2, or 3 ($F = 6.08$, $DF = 3$, $p = 0.001$) (Table 3).

Table 3: WW's punch and movement statistics by zone, mean $\pm$ standard deviation (95% confidence interval).

	Zone 1	Zone 2	Zone 3	Zone 4
Time (%)	51.1 $\pm$ 14.6 (47.9, 54.5)	38.8 $\pm$ 8.9 (35.6, 42.2)	8.9 $\pm$ 7.63 (5.7, 12.3)	0.98 $\pm$ 1.4 (-2.3, 4.3)
Punches/min	21.0 $\pm$ 7.2 (18.9, 23.7)	17.8 $\pm$ 7.3 (15.3, 20.5)	19.5 $\pm$ 27.2 (9.8, 29.4)	5.3 $\pm$ 15.7 (0, 11.0)
Metres/min	62.3 $\pm$ 8.75 (59.2, 65.5)	69.7 $\pm$ 10.9 (65.8, 73.7)	109.5 $\pm$ 58.0 (88.6, 130.4)	251.3 $\pm$ 485 (76.4, 426.1)

MW spent the same time in zones 1 and 2 ($p = 0.178$), and zones 1 and 3 ($p = 0.236$), more time in zone 2 than zone 3 ($p = 0.001$), and least time in zone 4 ($F = 35.21$, $DF = 3$, $p < 0.001$) (Figure 5). MW's PPM were equivalent to her opponents in zones 1 ($T = 0.66$, $DF = 56$, $p = 0.511$) and 4 ($T = -1.29$, $DF = 49$, $p = 0.202$), but less in zones 2 ($T = -4.15$, $DF = 42$, $p < 0.001$) and 3 ($T = -4.11$, $DF = 44$, $p < 0.001$). MW had the same PPM in all zones ($F = 2.16$, $DF = 3$, $p = 0.097$) (Table 4).

Table 4: MW's punch and movement statistics by zone, mean $\pm$ standard deviation (95% confidence interval).

	Zone 1	Zone 2	Zone 3	Zone 4
Time (%)	31.6 $\pm$ 19.9 (26.7, 36.6)	38.8 $\pm$ 10.8 (33.9, 43.7)	24.9 $\pm$ 14.4 (20.0, 29.9)	4.6 $\pm$ 4.8 (-0.35, 9.5)
Punches/min	18.7 $\pm$ 9.7 (15.1, 22.4)	14.6 $\pm$ 4.8 (12.8, 16.5)	14.0 $\pm$ 16.1 (8.0, 20.1)	9.2 $\pm$ 21.9 (1.0, 17.3)
Metres/min	66.1 $\pm$ 20.9 (58.3, 73.9)	67.9 $\pm$ 15.1 (62.2, 73.5)	76.7 $\pm$ 15.4 (70.8, 82.6)	236.5 $\pm$ 173.8 (171.6, 301.4)

5.3 Inside and Outside Boxers

MW spent 30% more time as the outside boxer ($T = -8.34$, $DF = 58$, $p < 0.001$), whereas WW spent equal time as the inside and outside boxer ($T = 1.51$, $DF = 62$, $p = 0.5$) (Table 5). MW and WW threw more PPM when they were the inside boxer than when they were the outside boxer (WW: $T = 2.17$, $DF = 61$, $p < 0.05$; MW: $T = 2.35$, $DF = 34$, $p < 0.05$). WW threw the same PPM as his opponent when inside ($T = 1.66$, $DF = 49$, $p = 0.104$), but more when outside ($T = -2.29$, $DF = 60$, $p < 0.05$). MW threw the same PPM as her opponent when inside ($T = -1.01$, $DF = 45$, $p = 0.319$), but fewer when outside ($T = -2.91$, $DF = 31$, $p < 0.01$). WW covered more metres per minute when outside than inside ($T = -3.21$, $DF = 58$, $p < 0.01$), whereas for MW there was no difference ($T = 1.26$, $DF = 37$, $p = 0.217$).

Table 5: WW's and MW's statistics by ring position relative to opponent.

		Inside	Outside
Time (%)	WW	53.4 ± 18.1 (46.9, 60.0)	46.6 ± 18.1 (40.0, 53.1)
	MW	33.6 ± 15.2 (27.9, 39.3)	66.4 ± 15.2 (60.7, 72.0)
Punches/min	WW	21.2 ± 6.7 (18.8, 23.7)	17.8 ± 6.2 (15.5, 20.0)
	MW	18.9 ± 12.0 (14.4, 23.4)	13.5 ± 3.7 (12.1, 14.8)
Metres/min	WW	66.0 ± 13.2 (61.2, 70.7)	78.0 ± 16.6 (72.0, 84.0)
	MW	83.8 ± 40.7 (68.6, 99.0)	73.7 ± 16.2 (67.6, 79.8)

5.4 First and Last minute

WW threw on average 3 more punches in the final minute of a round than the first ($T = -2.40$, $DF = 51$, $p < 0.05$), which matched the work rate of his opponents in both the first ($T = 0.74$, $DF = 61$, $p = 0.461$) and last ($T = -1.15$, $DF = 61$, $p = 0.256$) minutes of a round. MW threw 14 PPM ($T = -0.3$, $DF = 45$, $p = 0.757$) in the first (± 5.62) and last (± 3.16) minutes of a round. In the first minute of a round MW threw

the same number of punches as her opponents ($T = -4.40$, $DF = 54$, $p < 0.001$), but in the last minute she threw 5 fewer punches ($T = -3.46$, $DF = 36$, $p < 0.001$) (Figure 6).

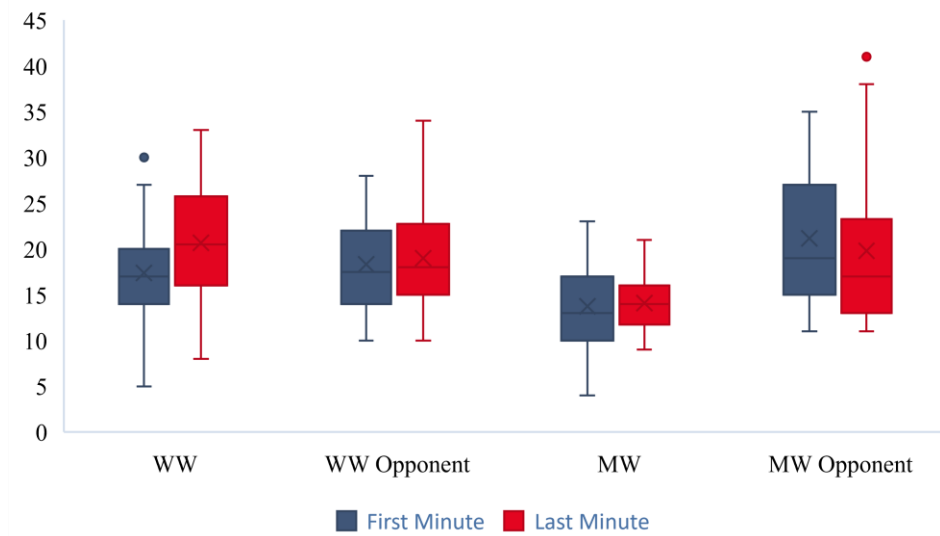


Figure 6: WW, MW, and opponents first- and last-minute punches.

In the first minute of a round WW covered 8 fewer metres than the last minute ($T = -2.11$, $DF = 58$, $p < 0.05$), and this level and increase in movement was matched by his opponents (first: $T = 0.88$, $DF = 61$, $p = 0.380$; last: $T = -0.15$, $DF = 55$, $p = 0.884$). MW covered 70 ± 21.6 metres in the first and last minutes of a round ($T = -1.55$, $DF = 57$, $p = 0.127$), which was the same as her opponents (first: $T = 0.98$, $DF = 57$, $p = 0.329$; last: $T = 1.39$, $DF = 57$, $p = 0.170$) (Figure 7).

WW ($T = -1.81$, $DF = 54$, $p = 0.077$) and MW ($T = -0.94$, $DF = 57$, $p = 0.349$) did not increase their success rates in the final minute compared to the first. WW's opponent's success rate did not change between first and last minute ($T = 121$, $DF = 56$, $p = 0.230$), however MW's opponent's success rate increased 11% in the last minute ($T = 2.65$, $DF = 56$, $p < 0.05$).

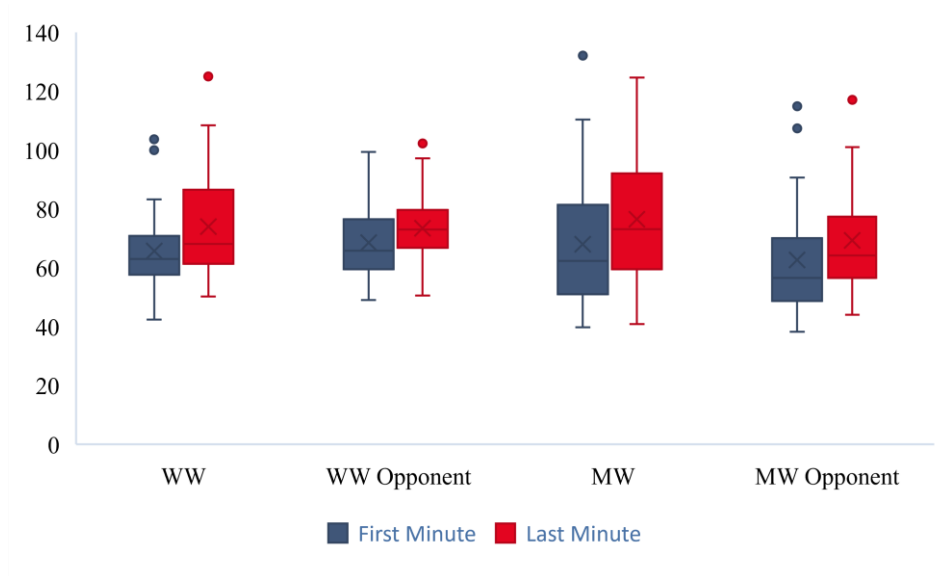


Figure 7: WW, MW, and opponents first- and last-minute metres.

5.5 Time in Attacking Range

WW and MW spent the same proportions of their time in the three attacking ranges (Chi-square = 480.214, DF = 2, $p < 0.001$, Cramer's $V = 0.04$) and threw the same proportion of punches whilst in each attacking range (Chi-square = 44.939, DF = 2, $p < 0.001$, Cramer's $V = 0.12$) (Figure 8).

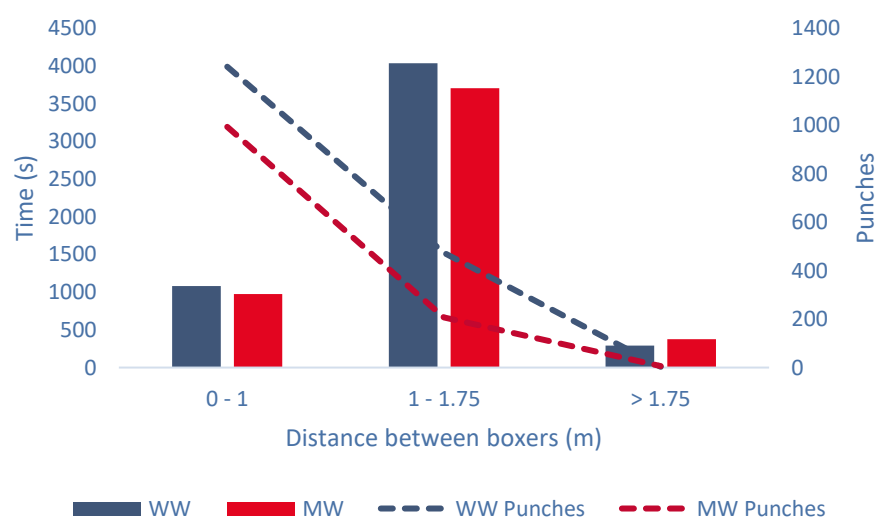


Figure 8: Time spent in different attacking ranges with number of punches thrown in each range by WW and MW.

6. Discussion

The activity level in a training environment was found to be the same for the same boxer in competitions, at around 20 punches per minute. This activity level was similar to activity levels established in previous studies (Davis et al. 2015; Davis et al., 2018; Thomas, 2015).

Contest winners have been found to have a higher punch success ratio than their opponents (Davis et al., 2015; Thomas, 2015). This study could not organise rounds into winners and losers because the videos were taken from a training environment without a referee, but it would be likely that the boxers in question would have won the majority of rounds because of their consistent competitive success, reflected in their world ranking. Both the middleweight and welterweight athletes had a higher success ratio than their opponents. The highest proportion of successful punches for the female boxer was thrown from greater than 1.5m away from her opponent, though this figure is calculated from a very small sample. The second highest proportion of successful punches for the female boxer was in the same category as the highest proportion of successful punches for the male boxer, 0.6 - 0.9m. The male boxer exhibited a clear reduction in success ratio with increasing distance, but the effect was less marked for the female boxer. This, in addition to the higher distance covered in a round, would suggest that the female boxer initiated punches from further away and, as such, her “attacking range” is broader than the male boxer’s. This could also partly explain her ability to win contests despite throwing fewer punches than her opponent – if she were to effectively transfer the momentum of her whole body’s movement in successful punches, they might be more likely to be seen as very successful punches which have been shown to be more common in unanimous winners (Thomas, 2015). Punch combinations were not included in this

study, but they have been shown to influence the judges' perception of which boxer is superior (Davis et al., 2015). The use of combinations could also have contributed to her success despite throwing fewer punches.

The average punches per minute and metres per minute for the male boxer matched that of his opponents, but the female boxer threw fewer punches and covered more distance. Both boxers had a higher success ratio than their opponents, but the female boxer still threw fewer successful punches per minute than her opponents. Scoring in boxing is based on more than just the number of punches landed in the target area, and the female boxer's success suggests that there are multiple approaches that may lead to a winning outcome. The need for an objective definition of boxing styles has been raised previously (Thomson & Lamb, 2016), and this study contributes to this effort.

The coaches working in the training centre painted lines on the ring canvas to help visualise how long boxers spent, and what they were doing, in each zone. This study provided a method to collect objective zonal data to facilitate discussion between athlete and coach. Both boxers spent most of their time in zones 1 and 2, but the proportion of time spent in each zone were different. The male boxer threw the same number of punches per minute as his opponent in all four zones, whereas the female boxer threw the same number as her opponent in zones 1 and 4, but fewer in zones 2 and 3. The increased activity level in zone 1 could be due to a need to defend the central position. The increased activity level in zone 4, could be motivated by a need to escape the vulnerable position of having no space to retreat backwards away from her opponent.

Controlling the centre of the ring has been suggested by coaches as a key indicator for success in a boxing contest. Both boxers had a higher activity level when they

were closer to the centre of the ring, and this was the same as their opponents. When further from the centre of the ring the male boxer threw more punches and covered more distance per minute than his opponent whereas the female boxer threw fewer punches and covered the same distance.

Activity level has been shown to reduce over the course of a fight on a round by round basis (Thomas, 2015), with winners landing more punches in round 3 than round 1 but activity levels reducing for all boxers between round 1 and round 3 (Davis et al., 2018). Sparring in training does not follow the same pattern of rounds against an opponent as competition, but this study evaluated how well boxers sustained their activity level within a round by comparing the first minute to the last minute. The female boxer maintained the same number of punches and distance covered and the male boxer increase in both punches thrown and distance. Both athletes had the same success ratio in the first and last minutes of a round, with the male's opponents also having the same success rate but the female's opponents increasing their success rate. It could be that the female boxer did not make as many blocking actions resulting in an increase in opponent success rate. Alternatively, it could be that the female boxer became predictable in her punching and movement actions and the opponent found more opportunities to land successful punches. A study with a larger data set could look at the sequences that lead to successful punches by boxer type, given the contextual information of relative position, punches thrown, and defensive actions made.

A meaningful difference was not found between the two boxers in terms of the proportion of time spent or the number of punches thrown in each of the three attacking ranges. Boxing can be thought of as an invasion sport, but the target area is attached to the opponent rather than being a fixed area in the field of play. If a

contest contains at least one front foot boxer, the time spent in different attacking ranges is likely to follow the same pattern. The agreement between boxers in terms of time in different attacking range is therefore unsurprising, but future work should try to incorporate contests that feature two back foot boxers.

The total distance covered by a boxer during a round may be symptomatic of a boxer's style but is likely to be of more interest to physiologists and strength and conditioning coaches than performance analysts in assessing the training stress accumulated by an athlete. Having an objective measure of the overall activity profile (punches thrown and distance covered) could be used to inform training plans, particularly when an athlete is returning from injury.

Perš et al. used previous location to split blobs. This would not work effectively in boxing as two players can come into contact and remain in contact for an extended period, possibly rotating together while this happens. Previous location can be used to guide the initial position of two boxers joined as one foreground object but cannot be relied upon for longer periods of grappling. In this study, foreground objects were also categorised by their colour information and this was used to separate a single object into the two boxers present.

The positional information generated by the bespoke system used in this study could be used to develop boxer profiles and understand baseline performance statistics for each boxer in the high performance system. Improved knowledge of their training performance and exertion level could inform training prescription as well as guiding return to training after an injury.

A limitation of this study is that only two boxers were included. To better understand the key features of different boxing styles a significantly larger group of boxers should be used to establish typical performance indicator levels representative of

different boxer types. The two boxers included in this study exhibited noticeably different movement strategies, but that does not suggest that these are the only movement strategies used by successful boxers. The intention of this study was not to define all boxing styles but to provide the methodology and a basis for more detailed study in the future.

One of the boxers included in the study did not have sufficient competition data to compare to the training data. It could be the case that her competition activity profile did not match the profile seen in training, and conclusions drawn were only applicable to training for that boxer. The reason for the lack of competition data was that the coaches were aware of her different style and were not interested in using resource on generating data about it. With more time in the elite training environment, and more competitions, a better assessment of the similarities between training and competition for that boxer could be made.

Another limitation is that the attacking ranges were not made specific to the boxers included. It is highly likely that a 52kg (flyweight) boxer would have a shorter reach than a 91+kg (super heavyweight). Further work should include more boxers from a range of weight categories in both genders to understand the relationship between a boxer's size, mobility, and effective punching range.

7. Conclusion

The aim of this study was to establish a tracking system and then use the system to analyse the activity profile of two highly successful elite amateur boxers in comparison to each other and their opponents. A reliable bespoke player tracker for overhead monocular video in boxing has been developed.

The activity level in sparring was consistent with competition in terms of punches per minute. The main finding of this study was that the two boxers exhibit clearly

different styles in the way that they occupy different areas of the ring and throw punches (in isolation and relative to their opponents). The female boxer consistently threw fewer punches and covered more distance than her opponent and spent more time in outer zones than the male boxer.

Of the different methods used to analyse the movement, the best agreement between boxers in terms of position, time, and punches thrown was found in terms of attacking range. Whilst the consistency of relative position is likely dependent on whether there is a front foot style boxer in the contest, the agreement on proportion of punches thrown by both boxers in each of the attacking ranges could be a discriminating factor between successful and unsuccessful boxers.

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9. Appendices

Appendix 1: Ethical Approval.



London Sport Institute REC

The Burroughs
Hendon
London NW4 4BT

Main Switchboard: 0208 411 5000

23/07/2020

APPLICATION NUMBER: 14510

Dear Jack Alexander Fairweather and all collaborators/co-investigators

Re your application title: Computer vision based tracking in boxing

Supervisor: Nimal David Nic Parmar Windridge James

Co-investigators/collaborators:

Thank you for submitting your application. I can confirm that your application has been given APPROVAL from the date of this letter by the London Sport Institute REC.

The following documents have been reviewed and approved as part of this research ethics application:

Document Type	File Name	Date	Version
Data Access Approval	EIS_LEGL_Ethics_MiddlesexUni_Signed_26022020		
GDPR Declaration	Data Protection Form	27/06/2020	1
Data Protection Act checklist	Data Protection Form	27/06/2020	1
Aims, objectives and hypotheses	Research Proposal V3	22/07/2020	3
Methods and data	Research Proposal V3	22/07/2020	1
Permission/Agreement Letter	EIS_LEGL_Ethics_MiddlesexUni_Signed_26022020	22/07/2020	1

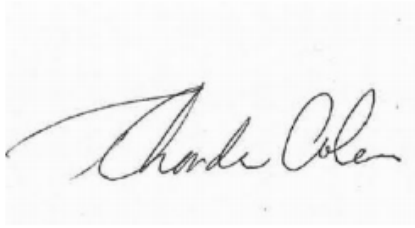
Although your application has been approved, the reviewers of your application may have made some useful comments on your application. Please look at your online application again to check whether the reviewers have added any comments for you to look at.

Also, please note the following:

1. Please ensure that you contact your supervisor/research ethics committee (REC) if any changes are made to the research project which could affect your ethics approval. There is an Amendment sub-form on MORE that can be completed and submitted to your REC for further review.
2. You must notify your supervisor/REC if there is a breach in data protection management or any issues that arise that may lead to a health and safety concern or conflict of interests.
3. If you require more time to complete your research, i.e., beyond the date specified in your application, please complete the Extension sub-form on MORE and submit it your REC for review.
4. Please quote the application number in any correspondence.
5. It is important that you retain this document as evidence of research ethics approval, as it may be required for submission to external bodies (e.g., NHS, grant awarding bodies) or as part of your research report, dissemination (e.g., journal articles) and data management plan.
6. Also, please forward any other information that would be helpful in enhancing our application form and procedures - please contact MOREsupport@mdx.ac.uk to provide feedback.

Good luck with your research.

Yours sincerely

A handwritten signature in black ink, reading "Rhonda Cohen". The signature is written in a cursive style with a large, sweeping initial "R".

Chair Dr Rhonda Cohen
London Sport Institute REC

Appendix 2: Minitab Export

1.1 Punches per minute in training and competition

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
Punches/minT WW	32	19.01	4.31	0.76
Punches/minC WW	38	18.51	8.44	1.4

Estimation for Difference

Difference	95% CI for Difference
0.50	(-2.64, 3.64)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
0.32	56	0.751

1.2 WW Punches per minute vs Opponent

Descriptive Statistics: Punches/min

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	18.64	4.82	0.85
WW	32	19.01	4.31	0.76

Estimation for Difference

Difference	95% CI for Difference
-0.36	(-2.65, 1.92)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-0.32	61	0.752

1.3 MW Punches per minute vs Opponent

Descriptive Statistics: Punches/min

MW/Other	N	Mean	StDev	SE Mean
MW	30	14.26	3.37	0.62
Opponent	30	20.67	7.02	1.3

Estimation for Difference

Difference	95% CI for Difference
-6.41	(-9.28, -3.54)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-4.51	41	0.000

1.4 WW Metres per minute vs Opponent

Descriptive Statistics: Metres/min

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	71.23	9.83	1.7
WW	32	70.0	11.7	2.1

Estimation for Difference

Difference	95% CI for Difference
1.24	(-4.16, 6.63)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
0.46	60	0.648

1.5 MW Metres per minute vs Opponent

Descriptive Statistics: Metres/min

MW/Other	N	Mean	StDev	SE Mean
MW	30	77.0	21.8	4.0
Opponent	30	64.0	14.4	2.6

Estimation for Difference

Difference	95% CI for Difference
13.05	(3.47, 22.64)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
2.74	50	0.009

1.6 WW Success ratio vs Opponent

Descriptive Statistics: Success Ratio

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	0.622	0.109	0.019
WW	32	0.725	0.105	0.019

Estimation for Difference

Difference	95% CI for Difference
-0.1035	(-0.1570, -0.0501)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-3.88	61	0.000

1.7 MW Success ratio vs Opponent

Descriptive Statistics: Success Ratio

MW/Other	N	Mean	StDev	SE Mean
MW	30	0.594	0.103	0.019
Opponent	30	0.541	0.133	0.024

Estimation for Difference

Difference	95% CI for Difference
0.0524	(-0.0091, 0.1140)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.71	54	0.093

1.8 WW Success per minute vs Opponent

Descriptive Statistics: Success/min

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	11.60	3.59	0.63
WW	32	13.89	4.03	0.71

Estimation for Difference

Difference	95% CI for Difference
-2.283	(-4.191, -0.374)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-2.39	61	0.020

1.9 MW Success per minute vs Opponent

Descriptive Statistics: Success/min

MW/Other	N	Mean	StDev	SE Mean
MW	30	8.44	2.43	0.44
Opponent	30	11.55	5.93	1.1

Estimation for Difference

Difference	95% CI for Difference
-3.11	(-5.48, -0.74)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-2.66	38	0.011

1.10 WW vs MW Success range

Chi-Square Test for Association: Worksheet rows, Worksheet columns

Rows: Worksheet rows Columns: Worksheet columns

	Hit - WW	Hit - MW	All
1	237	170	407
	260.26	146.74	
	2.080	3.688	
2	160	153	313
	200.15	112.85	
	8.056	14.288	
3	419	250	669
	427.81	241.19	
	0.181	0.321	
4	371	118	489
	312.70	176.30	
	10.869	19.279	
5	65	8	73
	46.68	26.32	
	7.189	12.750	
6	2	8	10
	6.39	3.61	
	3.020	5.357	
All	1254	707	1961

Cell Contents

Count

Expected count

Contribution to Chi-square

Chi-Square Test

	Chi-Square	DF	P-Value
Pearson	87.078	5	0.000
Likelihood Ratio	91.831	5	0.000

1 cell(s) with expected counts less than 5.

Chi-Square Test

	Chi-Square	DF	P-Value
Pearson	87.078	5	0.000
Likelihood Ratio	91.831	5	0.000

2 cell(s) with expected counts less than 5.

2.11 WW Time in zone

One-way ANOVA: Z1 %, Z2 %, Z3 %, Z4 %

Method

Null hypothesis All means are equal
Alternative hypothesis Not all means are equal
Significance level $\alpha = 0.05$
Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	4	Z1 %, Z2 %, Z3 %, Z4 %

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	3	54743	18247.8	206.84	0.000
Error	124	10940	88.2		
Total	127	65683			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
9.39268	83.34%	82.94%	82.25%

Means

Factor	N	Mean	StDev	95% CI
Z1 %	32	51.17	14.60	(47.88, 54.46)
Z2 %	32	38.87	8.90	(35.58, 42.15)
Z3 %	32	8.99	7.63	(5.70, 12.27)
Z4 %	32	0.976	1.479	(-2.310, 4.263)

Pooled StDev = 9.39268

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

Factor	N	Mean	Grouping
Z1 %	32	51.17	A
Z2 %	32	38.87	B
Z3 %	32	8.99	C
Z4 %	32	0.976	D

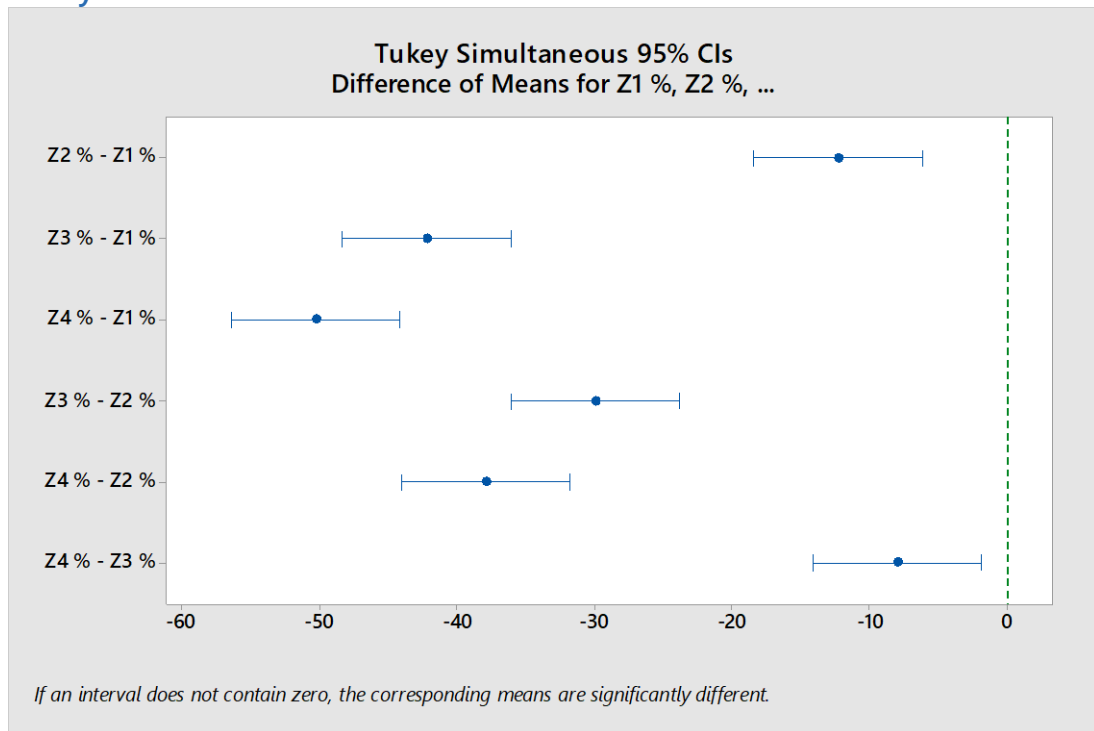
Means that do not share a letter are significantly different.

Tukey Simultaneous Tests for Differences of Means

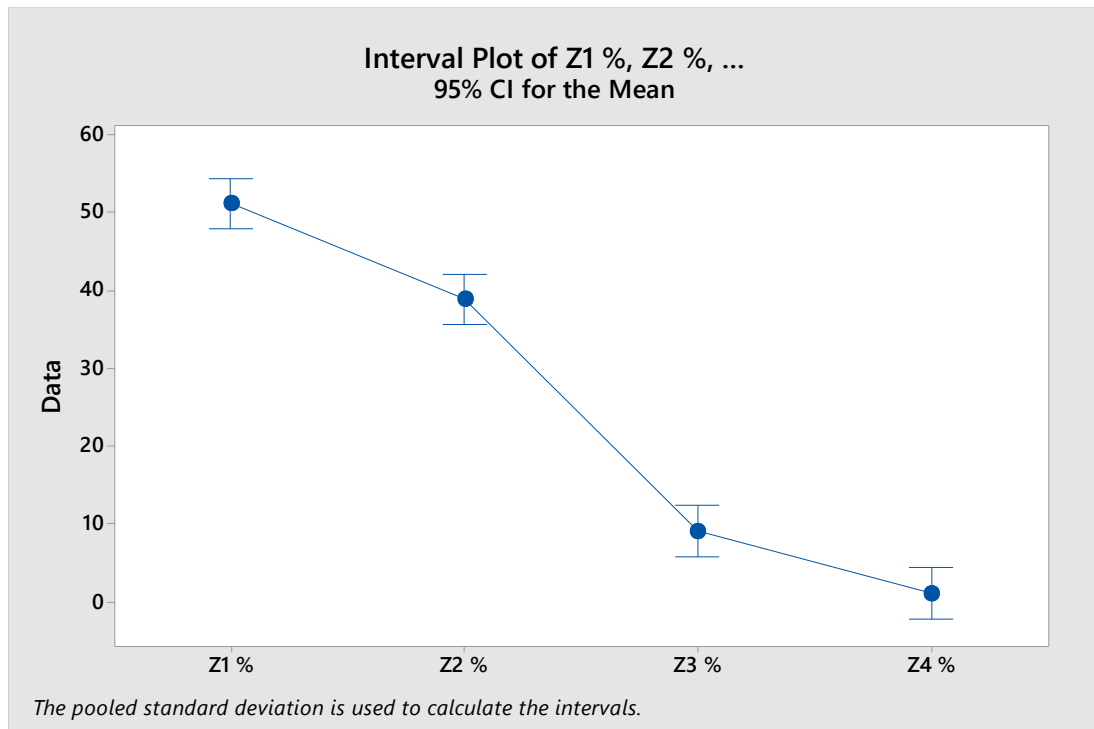
Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
Z2 % - Z1 %	-12.30	2.35	(-18.41, -6.19)	-5.24	0.000
Z3 % - Z1 %	-42.18	2.35	(-48.29, -36.07)	-17.96	0.000
Z4 % - Z1 %	-50.19	2.35	(-56.30, -44.08)	-21.38	0.000
Z3 % - Z2 %	-29.88	2.35	(-35.99, -23.77)	-12.73	0.000
Z4 % - Z2 %	-37.89	2.35	(-44.00, -31.78)	-16.14	0.000
Z4 % - Z3 %	-8.01	2.35	(-14.12, -1.90)	-3.41	0.005

Individual confidence level = 98.96%

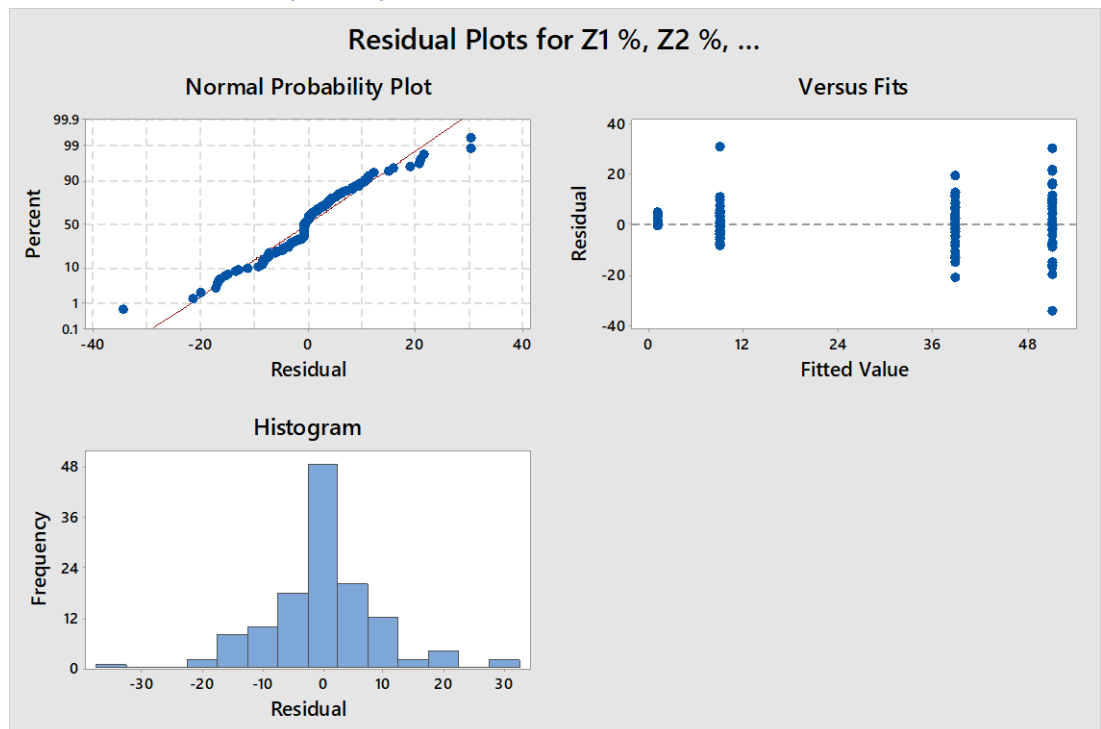
Tukey Simultaneous 95% CIs



Interval Plot of Z1 %, Z2 %, ...



Residual Plots for Z1 %, Z2 %, ...



2.12 MW Time in Zone

One-way ANOVA: Z1 %, Z2 %, Z3 %, Z4 %

Method

Null hypothesis All means are equal

Alternative hypothesis Not all means are equal

Significance level $\alpha = 0.05$

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	4	Z1 %, Z2 %, Z3 %, Z4 %

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	3	19571	6523.5	35.21	0.000
Error	116	21494	185.3		
Total	119	41064			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
13.6121	47.66%	46.30%	43.99%

Means

Factor	N	Mean	StDev	95% CI
Z1 %	30	31.64	19.88	(26.71, 36.56)
Z2 %	30	38.82	10.76	(33.90, 43.74)
Z3 %	30	24.97	14.39	(20.05, 29.90)
Z4 %	30	4.571	4.814	(-0.352, 9.493)

Pooled StDev = 13.6121

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

Factor	N	Mean	Grouping
Z2 %	30	38.82	A
Z1 %	30	31.64	A B
Z3 %	30	24.97	B
Z4 %	30	4.571	C

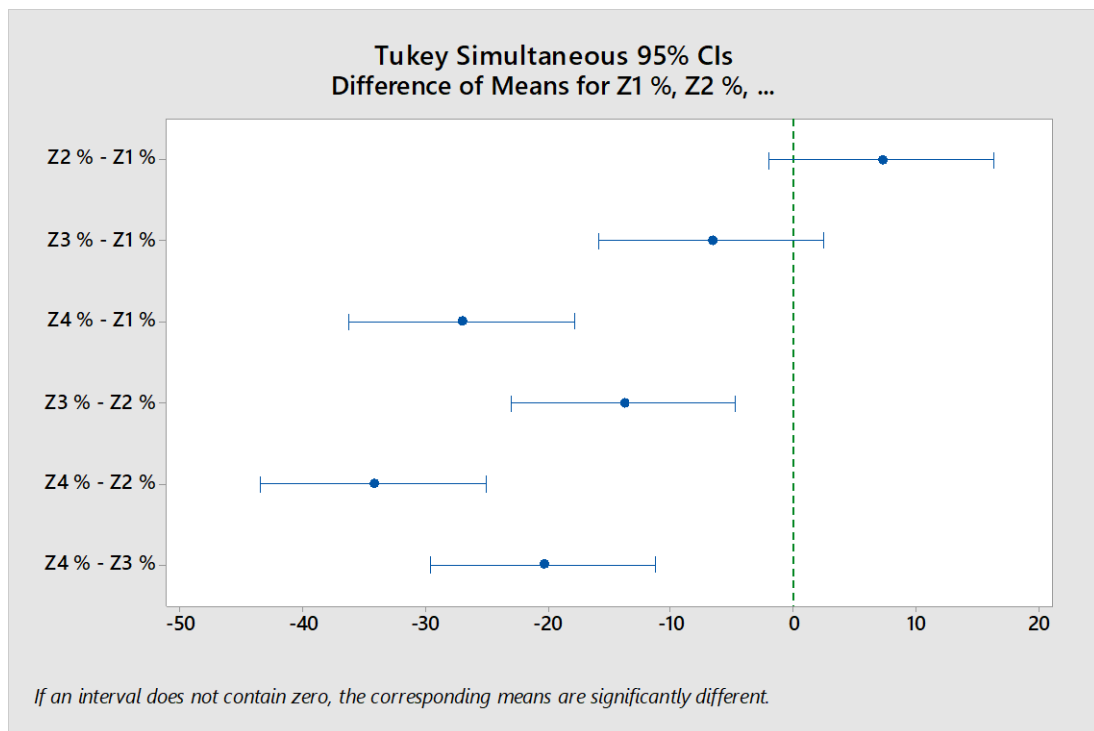
Means that do not share a letter are significantly different.

Tukey Simultaneous Tests for Differences of Means

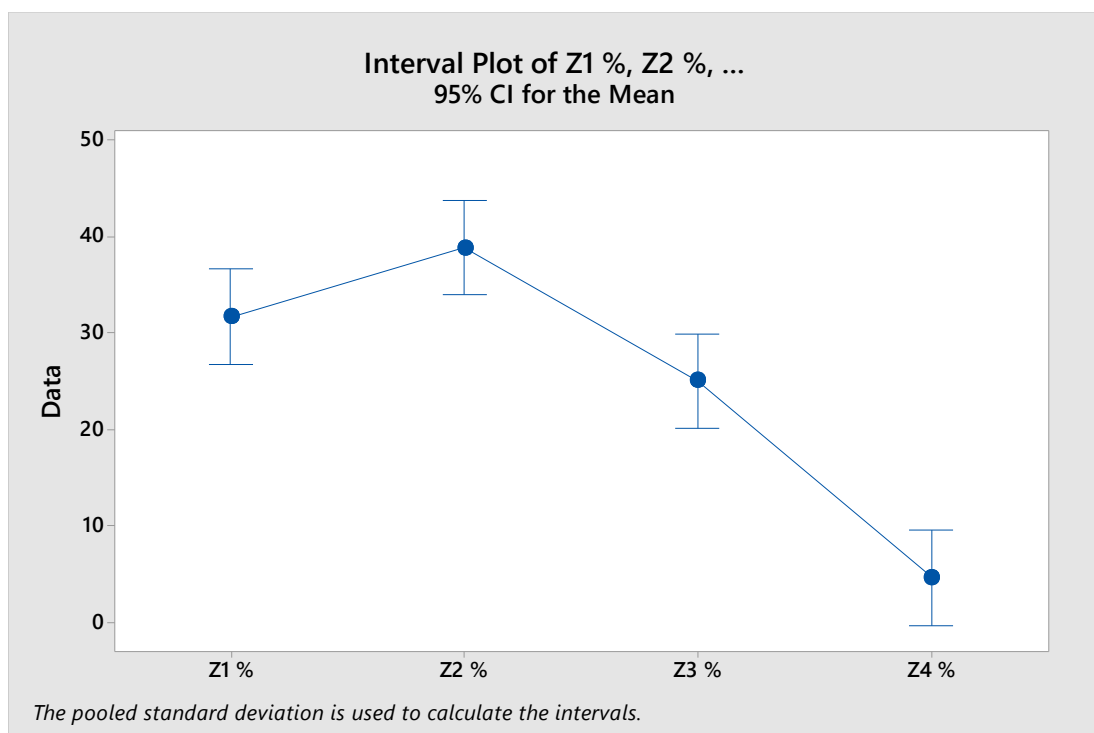
Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
Z2 % - Z1 %	7.18	3.51	(-1.99, 16.35)	2.04	0.178
Z3 % - Z1 %	-6.66	3.51	(-15.83, 2.51)	-1.90	0.236
Z4 % - Z1 %	-27.07	3.51	(-36.24, -17.90)	-7.70	0.000
Z3 % - Z2 %	-13.84	3.51	(-23.02, -4.67)	-3.94	0.001
Z4 % - Z2 %	-34.25	3.51	(-43.42, -25.08)	-9.74	0.000
Z4 % - Z3 %	-20.40	3.51	(-29.57, -11.23)	-5.81	0.000

Individual confidence level = 98.97%

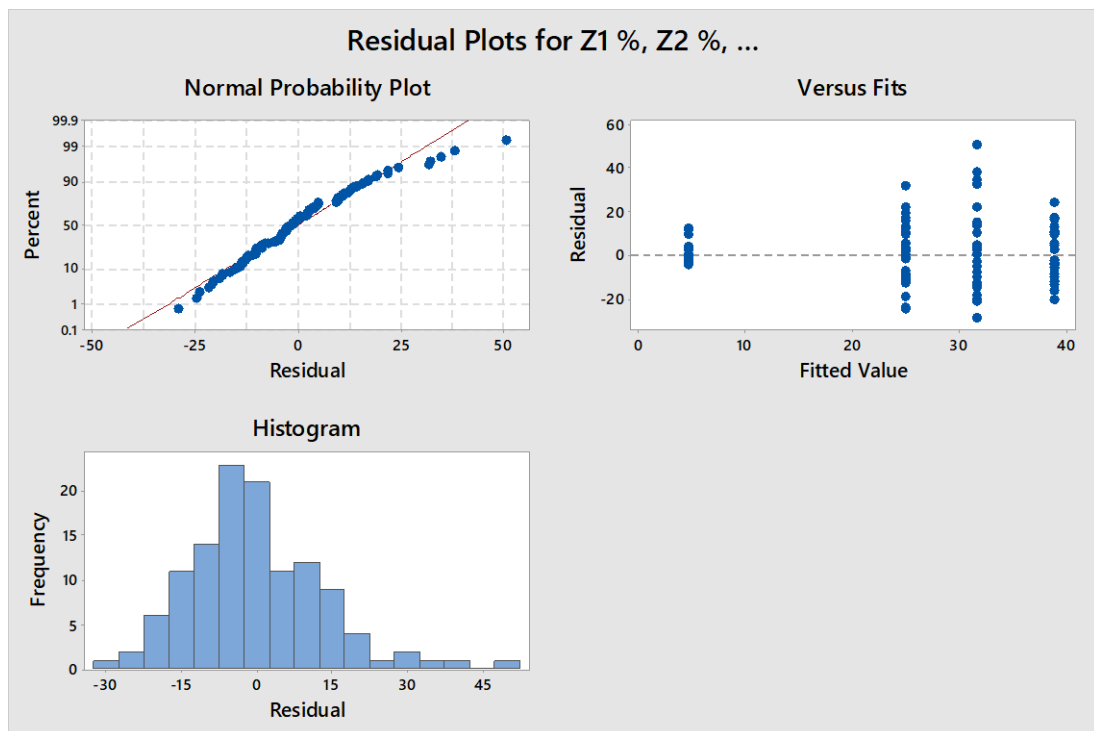
Tukey Simultaneous 95% Cis



Interval Plot of Z1 %, Z2 %, ...



Residual Plots for Z1 %, Z2 %, ...



2.13 WW vs MW Time in zone

Method

μ_1 : mean of WZ1 %

μ_2 : mean of MZ1 %

Difference: $\mu_1 - \mu_2$

Equal variances are not assumed for this analysis.

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
WZ1 %	32	51.2	14.6	2.6
MZ1 %	30	31.6	19.9	3.6

Estimation for Difference

Difference	95% CI for Difference
19.53	(10.60, 28.47)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
4.39	53	0.000

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
WZ2 %	32	38.87	8.90	1.6

MZ2 % 30 38.8 10.8 2.0

Estimation for Difference

95% CI for
Difference

0.05 (-4.99, 5.09)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value DF P-Value

0.02 56 0.985

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
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WZ3 %	32	8.99	7.63	1.3
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MZ3 %	30	25.0	14.4	2.6
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Estimation for Difference

95% CI for
Difference

-15.99 (-21.94, -10.03)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value DF P-Value

-5.41 43 0.000

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
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WZ4 %	32	0.98	1.48	0.26
-------	----	------	------	------

MZ4 %	30	4.57	4.81	0.88
-------	----	------	------	------

Estimation for Difference

95% CI for
Difference

-3.594 (-5.458, -1.731)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value DF P-Value

-3.92 34 0.000

2.14 WW Punches per minute by zone vs Opponent

Descriptive Statistics: Z1 P/min

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	22.49	9.23	1.6
WW	32	21.09	7.21	1.3

Estimation for Difference

Difference	95% CI for Difference
1.39	(-2.75, 5.54)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
0.67	58	0.504

Descriptive Statistics: Z2 P/min

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	17.27	6.33	1.1
WW	32	17.88	7.27	1.3

Estimation for Difference

Difference	95% CI for Difference
-0.61	(-4.02, 2.80)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-0.36	60	0.722

Descriptive Statistics: Z3 P/min

WW/Other	N	Mean	StDev	SE Mean
Opponent	31	16.2	12.3	2.2
WW	32	19.6	27.2	4.8

Estimation for Difference

Difference	95% CI for Difference
-3.36	(-14.02, 7.31)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-0.63	43	0.529

Descriptive Statistics: Z4 P/min

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	9.1	13.6	2.4
WW	32	5.3	15.8	2.8

Estimation for Difference

Difference	95% CI for Difference
3.73	(-3.64, 11.09)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.01	60	0.315

2.15 MW Punches per minute by zone vs Opponent

Descriptive Statistics: Z1 P/min

MW/Other	N	Mean	StDev	SE Mean
MW	30	18.75	9.76	1.8
Opponent	30	17.20	8.31	1.5

Estimation for Difference

Difference	95% CI for Difference
1.55	(-3.14, 6.24)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
0.66	56	0.511

Descriptive Statistics: Z2 P/min

MW/Other	N	Mean	StDev	SE Mean
MW	30	14.64	4.86	0.89

Opponent	30	22.79	9.59	1.8
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Estimation for Difference

Difference	95% CI for Difference
-8.15	(-12.11, -4.19)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-4.15	42	0.000

Descriptive Statistics: Z3 P/min

MW/Other	N	Mean	StDev	SE Mean
MW	30	14.1	16.1	2.9
Opponent	30	39.3	29.4	5.4

Estimation for Difference

Difference	95% CI for Difference
-25.20	(-37.55, -12.85)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-4.11	44	0.000

Descriptive Statistics: Z4 P/min

MW/Other	N	Mean	StDev	SE Mean
MW	30	9.2	21.9	4.0
Opponent	30	18.7	33.8	6.2

Estimation for Difference

Difference	95% CI for Difference
-9.50	(-24.27, 5.26)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
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-1.29 49 0.202

2.16 WW Punches per minute by zone

One-way ANOVA: Z1 P/min, Z2 P/min, Z3 P/min, Z4 P/min
Method

Null hypothesis All means are equal
Alternative hypothesis Not all means are equal
Significance level $\alpha = 0.05$

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	4	Z1 P/min, Z2 P/min, Z3 P/min, Z4 P/min

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	3	4985	1661.6	6.08	0.001
Error	124	33901	273.4		
Total	127	38886			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
16.5347	12.82%	10.71%	7.10%

Means

Factor	N	Mean	StDev	95% CI
Z1 P/min	32	21.09	7.21	(15.31, 26.88)
Z2 P/min	32	17.88	7.27	(12.10, 23.67)
Z3 P/min	32	19.59	27.20	(13.80, 25.37)
Z4 P/min	32	5.35	15.77	(-0.44, 11.13)

Pooled StDev = 16.5347

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

Factor	N	Mean	Grouping
Z1 P/min	32	21.09	A
Z3 P/min	32	19.59	A
Z2 P/min	32	17.88	A
Z4 P/min	32	5.35	B

Means that do not share a letter are significantly different.

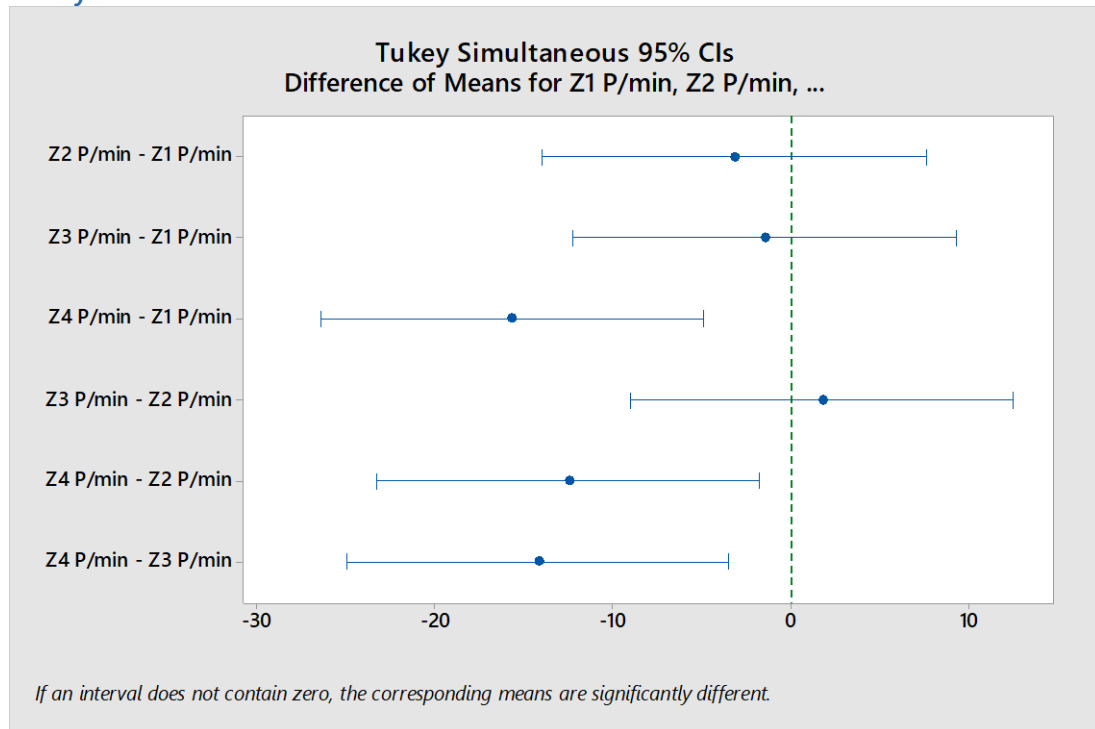
Tukey Simultaneous Tests for Differences of Means

Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
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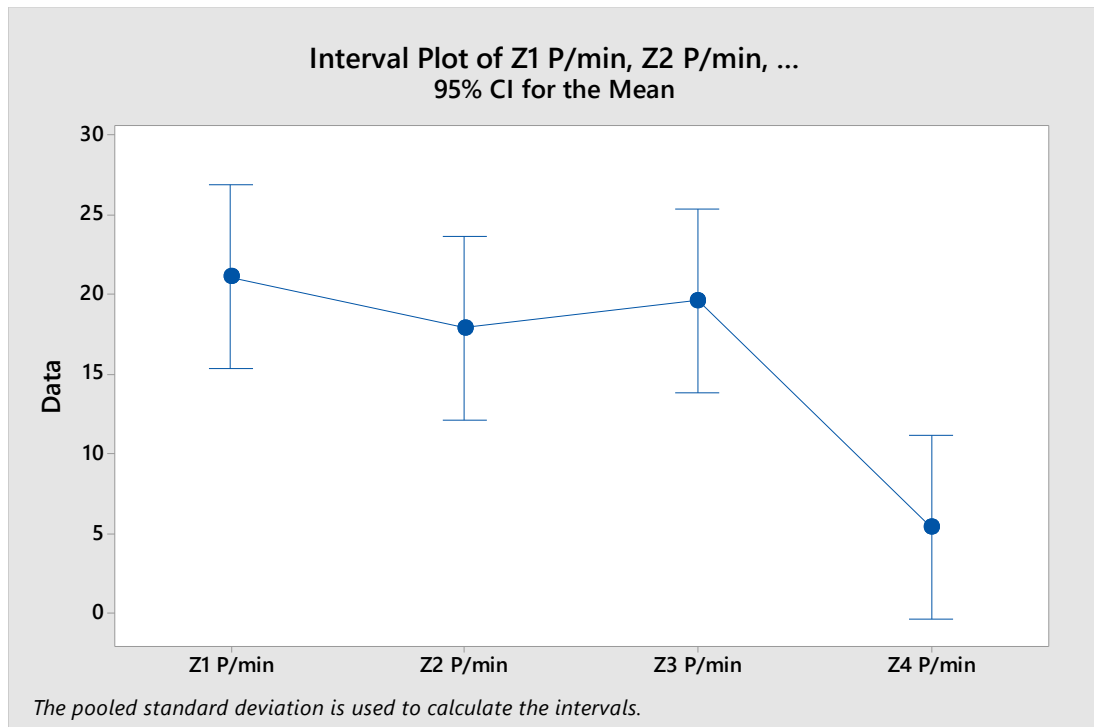
Z2 P/min - Z1 P/min	-3.21	4.13	(-13.97, 7.55)	-0.78	0.865
Z3 P/min - Z1 P/min	-1.50	4.13	(-12.26, 9.25)	-0.36	0.984
Z4 P/min - Z1 P/min	-15.74	4.13	(-26.50, -4.99)	-3.81	0.001
Z3 P/min - Z2 P/min	1.71	4.13	(-9.05, 12.46)	0.41	0.976
Z4 P/min - Z2 P/min	-12.53	4.13	(-23.29, -1.78)	-3.03	0.015
Z4 P/min - Z3 P/min	-14.24	4.13	(-25.00, -3.48)	-3.44	0.004

Individual confidence level = 98.96%

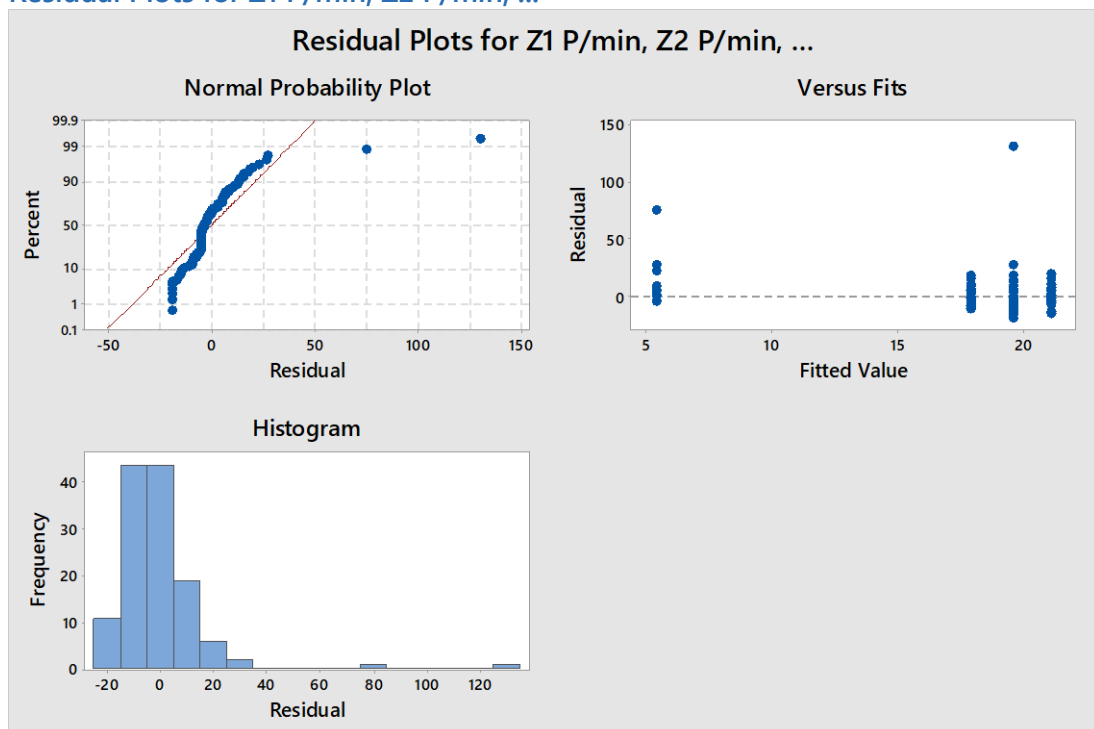
Tukey Simultaneous 95% CIs



Interval Plot of Z1 P/min, Z2 P/min, ...



Residual Plots for Z1 P/min, Z2 P/min, ...



2.17 MW Punches per minute by zone

One-way ANOVA: Z1 P/min, Z2 P/min, Z3 P/min, Z4 P/min Method

Null hypothesis All means are equal

Alternative hypothesis Not all means are equal

Significance level $\alpha = 0.05$

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	4	Z1 P/min, Z2 P/min, Z3 P/min, Z4 P/min

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	3	1389	463.1	2.16	0.097
Error	116	24874	214.4		
Total	119	26263			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
14.6433	5.29%	2.84%	0.00%

Means

Factor	N	Mean	StDev	95% CI
Z1 P/min	30	18.75	9.76	(13.45, 24.04)
Z2 P/min	30	14.640	4.862	(9.345, 19.936)
Z3 P/min	30	14.08	16.12	(8.79, 19.38)
Z4 P/min	30	9.16	21.89	(3.86, 14.45)

Pooled StDev = 14.6433

Tukey Pairwise Comparisons

Grouping Information Using the Tukey Method and 95% Confidence

Factor	N	Mean	Grouping
Z1 P/min	30	18.75	A
Z2 P/min	30	14.640	A
Z3 P/min	30	14.08	A
Z4 P/min	30	9.16	A

Means that do not share a letter are significantly different.

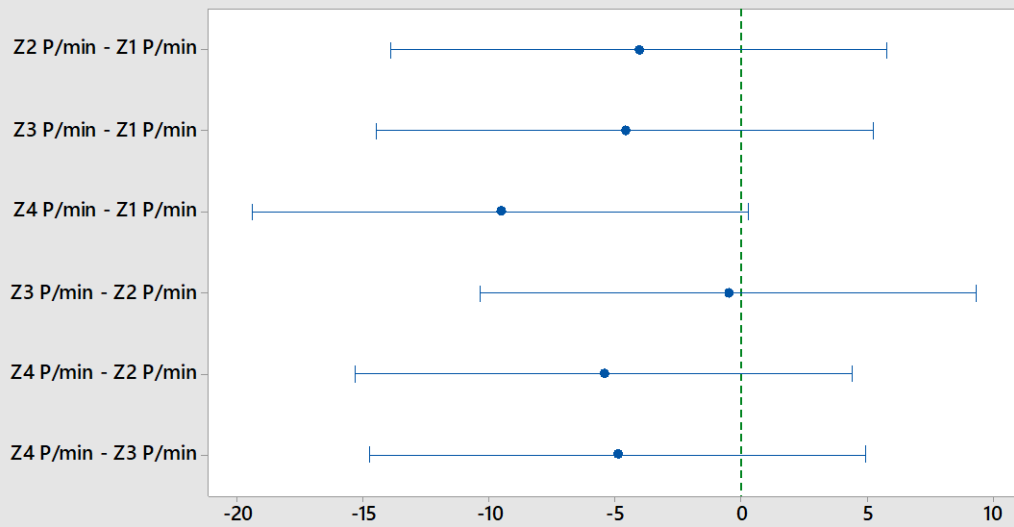
Tukey Simultaneous Tests for Differences of Means

Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
Z2 P/min - Z1 P/min	-4.11	3.78	(-13.97, 5.76)	-1.09	0.698
Z3 P/min - Z1 P/min	-4.67	3.78	(-14.53, 5.20)	-1.23	0.607
Z4 P/min - Z1 P/min	-9.59	3.78	(-19.46, 0.27)	-2.54	0.060
Z3 P/min - Z2 P/min	-0.56	3.78	(-10.42, 9.31)	-0.15	0.999
Z4 P/min - Z2 P/min	-5.48	3.78	(-15.35, 4.38)	-1.45	0.471
Z4 P/min - Z3 P/min	-4.92	3.78	(-14.79, 4.94)	-1.30	0.563

Individual confidence level = 98.97%

Tukey Simultaneous 95% CIs

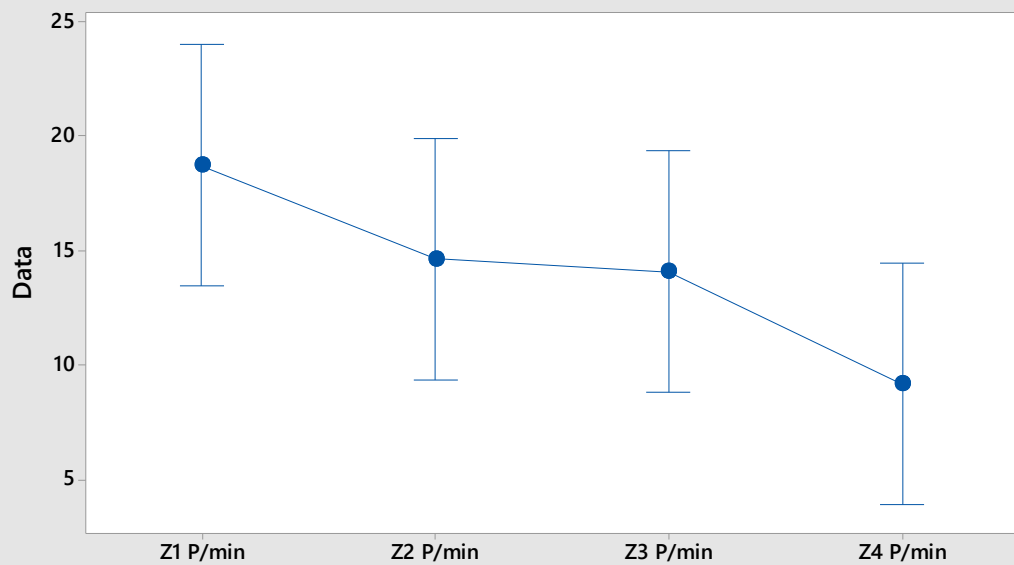
Tukey Simultaneous 95% CIs
Difference of Means for Z1 P/min, Z2 P/min, ...



If an interval does not contain zero, the corresponding means are significantly different.

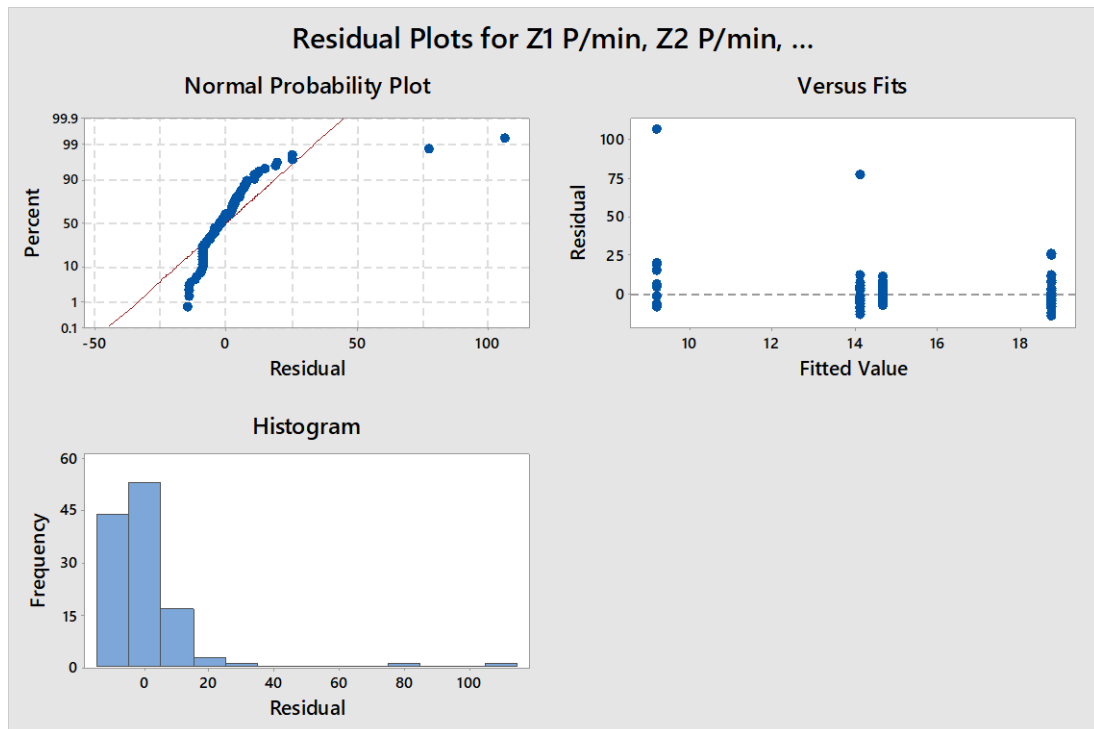
Interval Plot of Z1 P/min, Z2 P/min, ...

Interval Plot of Z1 P/min, Z2 P/min, ...
95% CI for the Mean



The pooled standard deviation is used to calculate the intervals.

Residual Plots for Z1 P/min, Z2 P/min, ...



2.18 MW Time inside/outside vs Opponent

Descriptive Statistics: % Time Inside

MW/Other	N	Mean	StDev	SE Mean
MW	30	33.6	15.2	2.8
Opponent	30	66.4	15.2	2.8

Estimation for Difference

Difference	95% CI for Difference
-32.75	(-40.62, -24.89)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-8.34	58	0.000

2.19 WW Time inside/outside vs Opponent

Descriptive Statistics: % Time Inside

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	46.6	18.1	3.2
WW	32	53.4	18.1	3.2

Estimation for Difference

Difference	95% CI for Difference
-6.83	(-15.89, 2.24)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-1.51	62	0.137

2.20 MW Punches per minute inside vs Opponent

Descriptive Statistics: P/min Inside

MW/Other	N	Mean	StDev	SE Mean
MW	30	18.9	12.1	2.2
Opponent	30	21.43	6.75	1.2

Estimation for Difference

Difference	95% CI for Difference
-2.54	(-7.62, 2.54)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-1.01	45	0.319

2.21 WW Punches per minute inside vs Opponent

Descriptive Statistics: P/min Inside

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	25.2	11.7	2.1
WW	32	21.25	6.68	1.2

Estimation for Difference

Difference	95% CI for Difference
3.95	(-0.84, 8.74)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.66	49	0.104

2.22 MW Punches per minute outside vs Opponent

Descriptive Statistics: P/min Outside

MW/Other	N	Mean	StDev	SE Mean
MW	30	13.47	3.69	0.67
Opponent	30	23.4	18.2	3.3

Estimation for Difference

Difference	95% CI for Difference
-9.90	(-16.82, -2.97)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-2.91	31	0.007

2.23 WW Punches per minute vs Opponent

Descriptive Statistics: P/min Outside

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	14.45	5.28	0.93
WW	32	17.75	6.22	1.1

Estimation for Difference

Difference	95% CI for Difference
-3.30	(-6.18, -0.41)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-2.29	60	0.026

2.24 MW Punches per minute inside vs outside

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
P/min Inside	30	18.9	12.1	2.2
P/min Outside	30	13.47	3.69	0.67

Estimation for Difference

Difference	95% CI for Difference
5.42	(0.74, 10.10)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
2.35	34	0.024

2.25 WW Punches per minute inside vs outside

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
P/min Inside	32	21.25	6.68	1.2
P/min Outside	32	17.75	6.22	1.1

Estimation for Difference

	95% CI for Difference
Difference	3.50 (0.27, 6.72)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
2.17	61	0.034

2.26 WW Metres per minute inside vs outside

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
Metres/min In	32	66.0	13.2	2.3
Metres/min Out	32	78.0	16.7	2.9

Estimation for Difference

	95% CI for Difference
Difference	-12.08 (-19.61, -4.55)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-3.21	58	0.002

2.27 MW Metres per minute inside vs outside

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
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Metres/min In	30	83.8	40.7	7.4
Metres/min Out	30	73.7	16.2	3.0

Estimation for Difference

Difference	95% CI for Difference
10.05	(-6.16, 26.25)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.26	37	0.217

2.28 WW Punches per minute, first vs last

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
First minute punches_1	32	17.38	5.15	0.91
Last minute punches_1	32	20.66	5.76	1.0

Estimation for Difference

Difference	95% CI for Difference
-3.28	(-6.01, -0.55)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-2.40	61	0.019

2.29 MW Punches per minute, first vs last

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
First minute punches_1	30	13.73	5.62	1.0
Last minute punches_1	30	14.10	3.16	0.58

Estimation for Difference

Difference	95% CI for Difference
-0.37	(-2.74, 2.00)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-0.31	45	0.757

2.30 WW Metres first minute vs Opponent

Descriptive Statistics: First minute metres

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	68.6	12.4	2.2
WW	32	65.7	13.5	2.4

Estimation for Difference

	95% CI for Difference
Difference	2.87 (-3.62, 9.35)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
0.88	61	0.380

2.31 WW Punches first minute vs Opponent

Descriptive Statistics: First minute punches

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	18.31	4.96	0.88
WW	32	17.38	5.15	0.91

Estimation for Difference

	95% CI for Difference
Difference	0.94 (-1.59, 3.46)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
0.74	61	0.461

2.32 WW Metres last minute vs Opponent

Descriptive Statistics: Last minute metres

WW/Other	N	Mean	StDev	SE Mean
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Opponent	32	73.4	12.3	2.2
WW	32	74.0	17.6	3.1

Estimation for Difference

	95% CI for Difference
-0.56	(-8.17, 7.06)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-0.15	55	0.884

2.33 WW Punches last minute vs Opponent

Descriptive Statistics: Last minute punches

WW/Other	N	Mean	StDev	SE Mean
Opponent	32	19.00	5.80	1.0
WW	32	20.66	5.76	1.0

Estimation for Difference

	95% CI for Difference
-1.66	(-4.54, 1.23)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-1.15	61	0.256

2.34 MW Metres first minute vs Opponent

Descriptive Statistics: First minute metres

MW/Other	N	Mean	StDev	SE Mean
MW	30	68.0	21.6	3.9
Opponent	30	62.7	20.1	3.7

Estimation for Difference

	95% CI for Difference
5.30	(-5.49, 16.09)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
0.98	57	0.329

2.35 MW Punches first minute vs Opponent

Descriptive Statistics: First minute punches

MW/Other	N	Mean	StDev	SE Mean
MW	30	13.73	5.62	1.0
Opponent	30	21.17	7.36	1.3

Estimation for Difference

Difference	95% CI for Difference
-7.43	(-10.82, -4.04)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-4.40	54	0.000

2.36 MW Metres last minute vs Opponent

Descriptive Statistics: Last minute metres

MW/Other	N	Mean	StDev	SE Mean
MW	30	76.6	21.1	3.9
Opponent	30	69.3	19.4	3.5

Estimation for Difference

Difference	95% CI for Difference
7.28	(-3.21, 17.77)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.39	57	0.170

2.37 MW Punches last minute vs Opponent

Descriptive Statistics: Last minute punches

MW/Other	N	Mean	StDev	SE Mean
MW	30	14.10	3.16	0.58

Opponent 30 19.80 8.44 1.5

Estimation for Difference

	95% CI for Difference
Difference	-5.70 (-9.04, -2.36)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-3.46	36	0.001

2.38 WW Metres per minute, first vs last

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
First minute metres_1	32	65.7	13.5	2.4
Last minute metres_1	32	74.0	17.6	3.1

Estimation for Difference

	95% CI for Difference
Difference	-8.30 (-16.16, -0.44)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-2.11	58	0.039

2.39 MW Metres per minute, first vs last

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
First minute metres_1	30	68.0	21.6	3.9
Last minute metres_1	30	76.6	21.1	3.9

Estimation for Difference

	95% CI for Difference
Difference	-8.55 (-19.60, 2.50)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-1.55	57	0.127

2.40 WW Opponent success rate first vs last minute

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
Last	32	62.9	11.1	2.0
First	32	58.9	15.4	2.7

Estimation for Difference

Difference	95% CI for Difference
4.08	(-2.66, 10.82)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
1.21	56	0.230

2.41 MW Opponent success rate first vs last minute

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
Last	30	60.2	14.9	2.7
First	30	49.2	17.2	3.1

Estimation for Difference

Difference	95% CI for Difference
11.01	(2.68, 19.35)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
2.65	56	0.011

2.42 WW Success rate first vs last minute

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
First Punch Success	32	68.9	17.0	3.0
Last Punch Success	32	75.5	11.7	2.1

Estimation for Difference

Difference	95% CI for Difference
-6.60	(-13.93, 0.73)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-1.81	54	0.077

2.43 MW Success rate first vs last minute

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
First Punch Success	30	56.1	18.1	3.3
Last Punch Success	30	60.3	16.8	3.1

Estimation for Difference

Difference	95% CI for Difference
-4.26	(-13.29, 4.77)

Test

Null hypothesis $H_0: \mu_1 - \mu_2 = 0$

Alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 0$

T-Value	DF	P-Value
-0.94	57	0.349

2.55 WW and MW time in attacking ranges

Chi-Square Test for Association: Worksheet rows, Worksheet columns

Rows: Worksheet rows Columns: Worksheet columns

	MW Ranges	WW Ranges	All
1	24347	27033	51380
	24827	26553	
	9.28	8.68	
2	92575	100836	193411
	93457	99954	
	8.33	7.79	

3	9411	7246	16657
	8049	8608	
	230.56	215.58	

All 126333 135115 261448

Cell Contents

Count

Expected count

Contribution to Chi-square

Chi-Square Test

	Chi-Square	DF	P-Value
Pearson	480.214	2	0.000
Likelihood Ratio	480.586	2	0.000

2.45 WW and MW Punches in attacking ranges

Chi-Square Test for Association: Worksheet rows, Worksheet columns

Rows: Worksheet rows Columns: Worksheet columns

	MW Punches in Ranges	WW Punches in Ranges	All
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1	993	1241	2234
	921.41	1312.59	
	5.562	3.905	

2	207	474	681
	280.88	400.12	
	19.432	13.641	

3	6	3	9
	3.71	5.29	
	1.410	0.990	

All 1206 1718 2924

Cell Contents

Count

Expected count

Contribution to Chi-square

Chi-Square Test

	Chi-Square	DF	P-Value
Pearson	44.939	2	0.000
Likelihood Ratio	46.035	2	0.000

1 cell(s) with expected counts less than 5.

2.46 Inter-Observer reliability

Attribute Agreement Analysis for Jess, Chris Between Appraisers Assessment Agreement

# Inspected	# Matched	Percent	95% CI
235	215	91.49	(87.16, 94.72)

Matched: All appraisers' assessments agree with each other.

Fleiss' Kappa Statistics

Response	Kappa	SE Kappa	Z	P(vs > 0)
*	-0.02845	0.0652328	-0.4361	0.6686
Backhand	0.93498	0.0652328	14.3330	0.0000
Jab	0.85522	0.0652328	13.1103	0.0000
L.Uppercut	-0.00213	0.0652328	-0.0327	0.5130
Lead Hook	0.93984	0.0652328	14.4074	0.0000
R.Uppercut	1.00000	0.0652328	15.3297	0.0000
Rear Hook	1.00000	0.0652328	15.3297	0.0000
Overall	0.85906	0.0474288	18.1127	0.0000

Cohen's Kappa Statistics

Response	Kappa	SE Kappa	Z	P(vs > 0)
*	-0.02003	0.0545124	-0.3675	0.6434
Backhand	0.93499	0.0652075	14.3387	0.0000
Jab	0.85529	0.0651737	13.1232	0.0000
L.Uppercut	0.00000	0.0000000	*	*
Lead Hook	0.93985	0.0651147	14.4338	0.0000
R.Uppercut	1.00000	0.0652328	15.3297	0.0000
Rear Hook	1.00000	0.0652328	15.3297	0.0000
Overall	0.85915	0.0473294	18.1527	0.0000

Appendix 3: Punch classification

The hand that the boxer used to throw the punch was classified as lead or rear. Jab, rear hand cross, inverted jab, and inverted rear hand cross punches classified as straight punches. Lead hook, rear hook, lead uppercut, and rear uppercut punches were classified as hook punches. The punches were also labelled according to the target area on the opponent, separated as either head or body targeted punches. The four classifications for each punch were combined into a four-character string, for example a successful lead hand straight punch targeting the head was recorded as “SLSH”.