# The Application of Data Analytics in Match and Kicking Performance in Elite Men's Rugby Union.

**Georgia Anne Scott ([redacted])**

Submitted to Swansea University in fulfilment of the requirements for the Degree of Doctor of Philosophy

Swansea University

2025

# Summary

Performance indicators are a key measure in analysing successful performance within Rugby Union. Their use has been documented in many different global competitions, including at the international level; however, research is scarce within the United Rugby Championship. There is a lack of general understanding of match performance at more detailed levels such as the sequence and action level across all competitions. Chapter 4 aimed to understand the associations between key performance indicators and match outcomes through the use of relative data and simplified modelling strategies. Results identified that increased relative kicking, metres made, and clean breaks, and decreased relative turnovers and scrum penalties conceded were associated with successful match outcomes. It was also established that relative data improved prediction accuracy, and simplification in model design did not degrade model accuracy. Chapter 5 aimed to interpret how relative kicking influences matches at the sequence level. This chapter established that in most sequences, a team only makes one additional kick than their opposition, confirming that relative kick values are built across many sequences within a single match. In Chapter 6, the aim was to investigate whether differences in kicking tactics exist between winning and losing teams. Results identified that despite kicking more, the distribution across the field and kick types was similar between winning and losing teams. Winning teams benefited from improved sequence outcomes when they utilised kicks in the red zone of the field. Chapter 7 aimed to interpret the spatiotemporal characteristics of kicks utilising K - Means clustering. Four key clusters emerged, which can be contextualised into ″fast″ and ″slow″ contestable kicks, and ″fast″ and ″slow″ territorial kicks. These studies combine to give a holistic understanding of kicking performance at the match, sequence, and action level, which can inform technical, tactical and physical performance.

# Declarations and Statements

## Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed [redacted] Date 26/03/2025

## Statement 1

This thesis is the result of my own investigations, except where otherwise stated and that other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

Signed [redacted] Date 26/03/2025

## Statement 2

I hereby give consent for my thesis, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organisations.

Signed [redacted] Date 26/03/2025

## Statement 3

The University's ethical procedures have been followed and, where appropriate, that ethical approval has been granted for the work contained within this thesis.

Signed [redacted] Date 26/03/2025

# Contents

# Acknowledgements

Firstly, I would like to thank my University supervisors Rowan Brown, Liam Kilduff, Neil Bezodis and Mark Waldron for all the help and support throughout my PhD and also for the opportunities you have given me to develop as a researcher outside of the PhD.

Rowan - Thank you for all the guidance, feedback and encouragement you have given me over the course of the PhD. From papers, to presentations, and even rugby teams, you've supported me through it all and I am extremely grateful for everything.

Liam - Thank you for all your support during the PhD and also for involving me in other projects across the Dept. I am also extremely thankful for your help in developing my career outside of research, never did I think I'd end the PhD running warm-ups at Thomond Park.

Mark - Thank you for all the valuable feedback and the opportunities to get involved with your research outside of Rugby. I would also like to thank you for all the conference support as these trips have been some of my fondest memories from my PhD.

Neil - Thank you for being an open door and sounding board across all things kicking and data visualisation. I am also very thankful for the opportunities to present and discuss data via EPS and Journal Club meetings, thank you for overseeing these.

I would also like to thank the Ospreys for not only funding the PhD, but also for embedding me within the team from day one. Specifically, I would like to thank Simon Church, for supervising the PhD and allowing me the freedom to develop this research across both the physical performance and rugby departments. I would also like to thank Aled Griffiths for his support in accessing data and for answering any questions I had. Furthermore, I would like to thank Toby Booth and all the coaches at the Ospreys for taking the time to engage with my research and for involving me in coaching conversations.

Thank you to my friends and fellow PGRs, you have made my time in Swansea very special. From office cricket, to Friday drinks, core lunches and run club, what a blast it has been. Jenny and Joe - thank you for being my first friends in Swansea and my long-suffering conference buddies! Freja - my Rugby buddy, thank you for involving me in your research and putting up with my terrible attempts at giving directions. Sam - thank you for being my friend in data, I've enjoyed our ongoing exchanges of cool graphs and coding problems! Robyn - thank you for bringing a sense of home to Swansea, I'll miss our early morning chats. I would also like to extend my thanks to my teammates at Seven Sisters RFC and my bootcamp pals.

Thank you to my family, for always being there for me. You've cheered my successes and supported me through the not-so-great moments. Gran - thank you for keeping me smiling and for your newly found love of Rugby. David - thanks for referring to me as your weird but clever sister. Dad - thanks for always being on the other end of the phone.

I'd like to dedicate this thesis to my Mum, who always believed in me but never got to see this adventure.

**Thesis Contributions** Georgia A. Scott designed the studies with support from M. Rowan Brown, Liam P. Kilduff, Neil E. Bezodis, Mark Waldron, Mark Bennett and Simon Church. Georgia A. Scott collected and analysed the data with support from M. Rowan Brown, Liam P. Kilduff, Neil E. Bezodis and Mark Waldron. Georgia A. Scott wrote the thesis. M. Rowan Brown and Liam P. Kilduff reviewed all chapters of the thesis and Neil E. Bezodis and Mark Waldron reviewed all experimental chapters.

# Publications and Conference Abstracts

Scott, G. A., Bezodis, N., Waldron, M., Bennett, M., Church, S., Kilduff, L. P., & Brown, M. R. (2023). Performance indicators associated with match outcome within the United Rugby Championship. Journal of Science and Medicine in Sport, 26(1), 63-68. https://doi.org/10.1016/j.jsams.2022.11.006

Scott, G. A., Bezodis, N.E., Waldron, M., Bennett, M., Church, S., Kilduff, L. P., & Brown, M. R. (2024) Interpreting Kick Dynamics in Professional Rugby Union Utilising Clustering Analysis. Presented at the 29th Annual Congress of the European College of Sport Science, July 2024. Glasgow, Scotland.

Scott, G. A., Bezodis, N.E., Waldron, M., Bennett, M., Church, S., Kilduff, L. P., & Brown, M. R. (2023) How winning teams kick for success in Rugby Union: A big data approach. Presented at the 28th Annual Congress of the European College of Sport Science, July 2023. Paris, France.

Scott, G. A., Bezodis, N.E., Waldron, M., Bennett, M., Church, S., Kilduff, L. P., & Brown, M. R. (2022) Performance indicators associated with match outcome within the United Rugby Championship. Presented at the 27th Annual Congress of the European College of Sport Science, September 2022. Seville, Spain.

# List of Figures

# List of Tables

# Abbreviations

| | |
|---|---|
| ANNs | Artificial Neural Networks |
| ANOVA | Analysis of Variance |
| CI | Confidence Interval |
| CSV | Comma Separated Values |
| L | Loss |
| MDA | Mean Decrease Accuracy |
| MRMR | Maximum Relevance, Minimum Redundancy |
| n | Sample Size |
| OOB | Out of Bag |
| PA | Points Against |
| PD | Points Difference |
| PF | Points For |
| PI | Performance Indicators |
| TSA | Total Score of Athleticism |
| URC | United Rugby Championship |
| W | Win |
| WSS | Total Within Sum of Squares |
| XML | Extensible Markup Language |

# 1 Introduction

After the introduction of professionalism to Men's Rugby Union (hereafter referred to as rugby) in 1995 (Hill et al., 2018), there has been an increased need to understand the technical, tactical and physical performance across the game. With changes in anthropometrics (Hill et al., 2018), laws (World-Rugby, 2017b) and other developments in the modern game, researchers must continue to develop and understand key areas of performance within the sport. Research within rugby spans many different themes, including physical performance, injury management and biomechanics, at both the club and international level, globally.

A key area of contemporary research is performance analysis, predominantly through methods analysing performance indicators (PIs) measured through video analysis (Colomer et al., 2020). These PIs are collected on video and coded by analysts in games, with many different metrics collected depending on the interests of the team or coaches. These PIs feature often in research comparing winning and losing teams, to underpin what drives successful performances and aid training direction. Studies have reported different key PIs across many competitions globally, including at the international and club level (Colomer et al., 2020). For example, different attacking metrics have been identified such as clean breaks (Bennett et al., 2019; Mosey & Mitchell, 2020), metres made and ball carry effectiveness (Bennett et al., 2019, 2020; Bunker & Thabtah, 2019; Mosey & Mitchell, 2020). Equally, the importance of set piece success has been highlighted in many competitions, predominantly lineout success (A. Hughes et al., 2017) and scrum penalties (Mosey & Mitchell, 2020). Kicking in play has also been identified as linked to successful performances (Bennett et al., 2019, 2020; A. Hughes et al., 2017), and conversely, turnovers conceded were also established as an indicator of unsuccessful teams (Mosey & Mitchell, 2020).

Traditionally, studies researching PIs focus on isolated data, where the frequency of PIs is solely analysed in isolation from their opposition. Authors have suggested recently that utilising differentials between teams may be a better description of the contest (Bennett et al., 2019). Therefore, a recent development within performance research in rugby is the use of relative data within match prediction to improve modelling efficiency. Bennett et al. (2019) utilised PIs in the context of the opposition rather than using absolute values, within Premiership Rugby. For example, if Team A made 200 m during a game and Team B made 400 m, the relative metres made for each team would be -200 m and 200 m respectively. This method improved model prediction rates and the relative values can be used to find the optimal value of PIs, that is, where completing additional actions over the opposition does not gain any further likelihood of winning. Bennett et al. (2020) repeated this methodology on data from the group and knockout phases of the 2015 World Cup, with similar improvements in prediction reported in comparison to absolute values. In contrast, Mosey and Mitchell (2020) identified no significant difference in relative and absolute modelling prediction when this methodology was repeated on sub-elite rugby within Australia, suggesting that this benefit may not be seen in lower levels of competition.

Within the game, despite significant research into PIs associated with successful performances, there is limited research to understand why PIs are linked to success and how teams can utilise them within a training and match setting. Studies are consistently reported at the match level (Colomer et al., 2020), which gives little context to what decision-making can be made on field to support the improvement of a certain PI. However, some authors have analysed performance in further detail than the match level, such as researching at the sequence (a period between the ball going in and out of play) or phase (a period between rucks within a sequence) level to give greater context (Bunker et al., 2021; Watson et al., 2020), however, these studies are limited and many utilise complex methodologies that limit the practical application of results given. Further detailed analysis of shorter durations of play, such as phases, sequences or possessions is more likely to drive insights that can be linked to actionable change within a practical environment. Equally, there is extremely limited research into the spatiotemporal characteristics of PIs and how this can be utilised to improve the physical performance linked to actions within games. Without this further in-depth understanding, it can be difficult to implement changes based on the results surrounding the key PIs.

The majority of research within rugby is limited to the international game, which is the highest level played worldwide (Colomer et al., 2020). It is unknown whether the results of studies based on the international level are applicable at the club level, given the differences in both playing standards, scheduling, frequency of games, opponents and many other features. To date, there is no research within the United Rugby Championship (URC) and very limited research available within its predecessors, the Pro14, Pro12, Magners and Celtic Leagues. With the majority of research into the club game focussed on the English Premiership (Bennett et al., 2019), Super Rugby (Coughlan et al., 2019) and the Japanese Top League (Bunker & Spencer, 2021). Given the URC's unique position as a global tournament, covering teams in Ireland, Italy, Scotland, South Africa and Wales, research in this competition is of great interest to the rugby community.

Within rugby, different analytics techniques have been used across performance to interpret datasets in different competitions. From machine learning (Bennett et al., 2019, 2020; Bunker & Thabtah, 2019), hypothesis testing (A. Hughes et al., 2017; M. T. Hughes et al., 2012) and clustering analytics (Coughlan et al., 2019), many methods have been utilised to interpret successful performances. Given the increase in availability and complexity of data, it is important to select the appropriate methodology for analysis, and ensure that the application of this methodology allows practical results that can be interpreted by practitioners and implemented within an elite rugby environment.

Understanding the technical, tactical and physical performance is key to developing a structured training plan from a team perspective as well as at the individual player level. Currently, the literature lacks detailed analysis that considers successful performance from a team and match level, including its application to decision-making from groups of players at the sequence level, and equally at an individual level. Furthermore, linking performance analysis metrics to physical performance has been underdeveloped in research. Therefore, there is the opportunity, given increases in spatiotemporal data, to include greater physical context to PIs available. With the growing availability of data, it is key to utilise this to create and answer performance questions at a team, group and individual level, which can then be used to inform coaching decisions and programming. Given the increase in complexity of data and the growing application of different analytical methods, there is an opportunity to apply these methods in datasets from the URC and drive an optimal methodology of understanding successful performance at the match, sequence and individual level.

Therefore the aims of this thesis were the following:

1. Understand key performance indicators associated with match outcomes in the United Rugby Championship. (Chapter 4)

   Chapter 4 will utilise match level data to understand whether relative performance indicators improve model efficacy. From this, this study will also examine which indicators are strongly associated with match outcome and whether the number of indicators used in modelling can be simplified without causing a deterioration in model performance.

2. Interpret how relative kicking influences matches at the sequence level. (Chapter 5)

   Within Chapter 5, sequence level data will be analysed to interpret whether the success of relative kicking at the match level can be demonstrated across sequences within a match. This includes analysis of different kick types and positive, neutral and negative sequence outcomes.

3. Investigate whether differences exist in kicking tactics between winning and losing teams. (Chapter 6)

   In this chapter, the different kick types and zones utilised for kicking will be investigated to understand whether differences exist between winning and losing teams. Sequence level data will also be utilised to interpret whether winning teams gain better sequence outcomes from kicking, i.e do winning teams just kick more or do they also kick better?

4. Assess the spatiotemporal characteristics of kicks to inform the physical demands of a successful kick chase. (Chapter 7)

   Finally, Chapter 7 will utilise action level data to analyse individual kicks. This analysis includes the spatiotemporal characteristics such as distance, gain, collection time and speed, whilst also examining different kick types, zones, outcomes and following actions.

   A flow diagram has been included to illustrate the flow of this thesis.

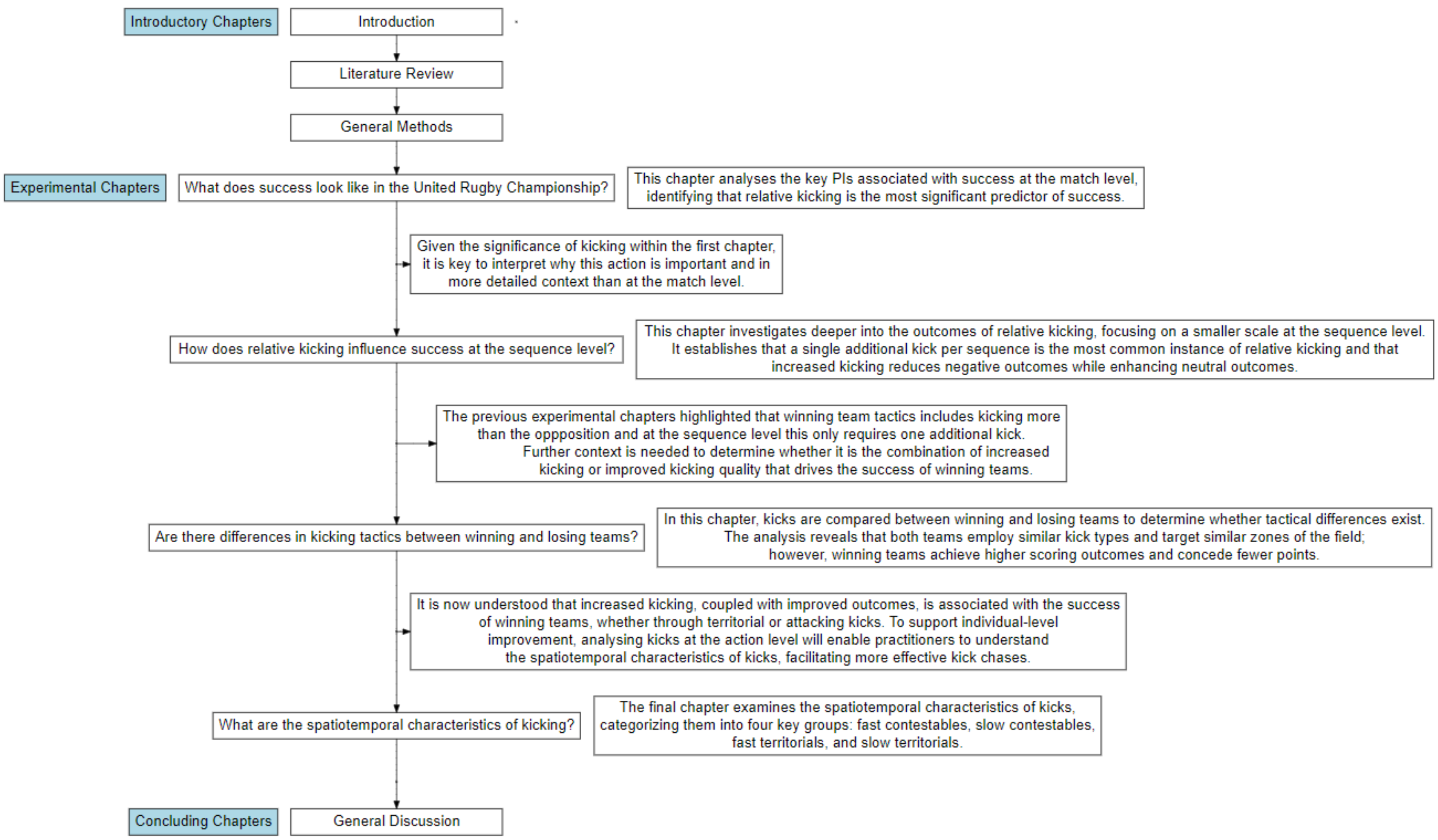



**Figure 1.1**
Flow diagram showing the description of each experimental chapter and the link between each chapter.

# 2 Literature Review

## 2.1 Introduction

Rugby is a team collision sport played by over 8 million men, women and children globally (World-Rugby, 2017b). In 1995, professionalisation began for Men's rugby (Hill et al., 2018), leading to a greater need to understand technical, tactical and physical performance in the game, and how coaches, teams and individuals can optimise this. In the modern day, data is now available to monitor players from many different perspectives, including strength, conditioning, tactical performance and injury surveillance. The increasing availability of larger and more varied datasets supports the increased reliability of data as a decision-support tool within the sport and allows the development of new performance questions to ask of the data itself.

One key area of interest within the research into rugby is performance analysis, with many studies utilising video analysis data to not only assess overall team and individual performance but also understand what factors drive winning performances (Colomer et al., 2020). This data allows analysts and coaches to get feedback on teams and individuals and can further influence and support tactical, technical and physical performance training direction (M. D. Hughes & Bartlett, 2015). In addition, this data can be analysed across a match, to understand overall performance, in sequence, to understand play to play decision making, and finally on an individual action, to understand the impact of a single action by a player. This can be combined to understand the full breadth of performance from a team to an individual.

Over time, there have been many changes across the game including law reforms (World-Rugby, 2017a) and the physical attributes of the players themselves (Hill et al., 2018). The ongoing changes mean that it is important for both researchers and practitioners to keep up to date about their understanding of game performance across seasons. Equally, it has been previously reported that performance analysis knowledge specifically, does not necessarily transfer across different competitions (Watson et al., 2017).

This literature review will cover the current state of research in performance analysis within rugby, covering the match level (Chapter 4), data transformations and methods (Chapter 4), understanding matches at different levels (Chapters 5 and 6) and kicking and other skills research (Chapter 7). This review will aim to understand the current literature surrounding performance frameworks and how these can be built to understand and support player and team performance, by combining the link between match, sequence and action level. Finally, this chapter will aim to understand the current state of complexity within team field sports and how this is utilised for performance question setting.

## 2.2 Performance Indicators at the Match Level

Performance indicators (PIs) are action variables selected to define an aspect of performance within sport (M. D. Hughes & Bartlett, 2015). To be considered useful to coaches and analysts, these PIs should link to an important match outcome (M. D. Hughes & Bartlett, 2015). Efforts have been made in the past to standardise the depiction of team and position-specific PIs (James et al., 2005; Jones et al., 2008), with authors coordinating with coaching staff to derive a global list of behaviours for both team and positional performance. Despite this, a large selection of PIs exist across studies throughout the literature, across many competitions in the global game (Colomer et al., 2020).

Predicting match outcomes in rugby based on these PIs has been researched by many authors (Colomer et al., 2020). The topic is of interest to both academic researchers and rugby practitioners as it assists in understanding what indicators are useful and may influence future training and tactical planning. Data is dynamic and indicators are collected via video footage which can produce error and subjectiveness in their nature. Furthermore, much of the research that has been done, both in predicting match outcomes and in aspects of interest in rugby, has been limited to international rugby (Bennett et al., 2020; A. Hughes et al., 2017; M. T. Hughes et al., 2012). There has been limited analysis in elite club-level rugby worldwide (Bennett et al., 2019), with no named analysis within the United Rugby Championship (formerly the Pro14).

Many PI studies tend to analyse large groups of PIs when building models (Colomer et al., 2020). This is beneficial as it gives a wide scope of understanding of the game, however, reporting several significant variables may confuse messaging and impact the practical application of these results. Furthermore, PIs are often collected using different methods and can be subjective in terms of what is being measured. In addition to this, different groups are likely to collect different PIs to analyse, which can confuse comparisons across competitions and levels (Colomer et al., 2020). For example, some authors may use global sports providers such as OPTA (Bennett et al., 2019, 2020; Bunker & Spencer, 2021) whereas other authors may collect their PIs from national bodies (Cunningham et al., 2018). This is not a novel experience within rugby, with other sports suffering from the same issue of multiple PIs and also subjectiveness or lack of definition in measurements (Prieto et al., 2015; Sarmento et al., 2018). Key themes, rather than PIs themselves, may be utilised when comparing studies to ensure corroboration across different research.

Key themes identified when comparing winning and losing performances tend to sit within certain areas of the game including attacking metrics, kicking, set piece and infringements. Attacking metrics, such as carrying ability, clean breaks and metres made, are presented throughout research into the relationship between match outcomes and performance indicators (Bennett et al., 2019, 2020; Bunker & Spencer, 2021). Increased metres made, average carry metres and clean breaks are generally associated with winning outcomes for teams in many competitions (Bennett et al., 2019, 2020; Bunker & Spencer, 2021). These results are intuitive given rugby's history as an invasion-evasion game. It is important for teams to gain territory across the field, through successful possession phases.

Another key concept for gaining territory within the game is through the use of kicking from hand. Kicking has been highlighted in many studies as an indicator of success across multiple competition levels (Bennett et al., 2020; Bishop & Barnes, 2013; A. Hughes et al., 2017; Mosey & Mitchell, 2020). Results suggest kicking from hand more than the opposition is key to success (Bennett et al., 2019, 2020), as well as kicking for touch or possession (Vaz et al., 2011). There is also suggestions that kicking within the opposition half is important when it comes to match success (Bishop & Barnes, 2013). Kicking is a less intuitive method of success within rugby, given that kicking the ball away will gain territory but with the risk of losing possession to the opposition.

Set piece is repeatedly identified as a predictor of match success, however, it is predominantly lineout success reported compared to scrum success (Bennett et al., 2020; Bunker & Spencer, 2021; A. Hughes et al., 2017). Lineouts are a large part of the game, as a starting point for attacking phases. Hence, the ability to be successful within your own lineout and disrupt your opposition's lineout is key.

Arguably scrums may be more important regarding infringements, where scrum penalties have been identified as a marker of losing performances (Mosey & Mitchell, 2020). Infringements, predominantly penalties rather than free kicks, are repeatedly identified as markers of losing performances (Bennett et al., 2020; Bishop & Barnes, 2013; A. Hughes et al., 2017). This is intuitive given a penalty allows a team the opportunity to score points or kick for territory, and gain possession via a lineout. Many authors also report a spatial relevance to these penalties, with penalties in the opposition half (Bishop & Barnes, 2013), and particularly the opposition 22 m identified specifically as indicators of losing performances (Bennett et al., 2020).

Close games are another area of interest within performance analysis. These games have been examined by Vaz et al. (2011), who utilised clustering analysis to justify whether a game was considered close, balanced or unbalanced. This is in place of the standard term for a close game, where a team loses by 7 points or less and therefore gains a bonus point in competitions (United Rugby Championship, 2025). Close games were defined as either being won or lost by 11 or 15 points. The former, 11 points was the value used for Super 12 games ($n = 204$), whereas the latter denoted the value used for international games ($n = 120$). Analysis was completed separately for each group to preserve differences between the international and club games. In the club games, it was reported that winning teams opted for a more territorial-based approach, with teams kicking the ball and following up defensively. Conversely, authors did not find any significant differences between international fixtures across all PIs. This may suggest that close games at the international level are more competitive, with similar abilities within teams compared to the club level.

Authors have suggested that PIs are not consistent across different competitions, and that very few PIs could be used to monitor winning performance across multiple competitions in rugby (Watson et al., 2017). The authors question that if a PI cannot be translated across competition, it may not be useful for analysis. Different competitions and levels of the sport are likely to have different skill levels, team match-ups and player availability, which in turn is likely to change playing styles and therefore impact the PIs which lead to success. These differences in PIs have been reported both by Watson et al. (2017) and Vaz et al. (2011), and given the lack of research previously highlighted within the URC, they provide scope to produce similar analysis to understand what drives success within this competition specifically.

Authors highlight that without the greater context of the game at hand, many absolute values of PIs may not provide enough context to make improvements via coaching (M. T. Hughes et al., 2012). For example, M. T. Hughes et al. (2012) identified that there is a lack of context around kicking metrics, for example place kick difficulty, highlighting the need to include further context surrounding PIs. Similar arguments are given around the line break opportunities, where without the outcome of the actions at the sequence level (e.g. a try or other outcome), the data has limited use to coaching staff. This concept has also been discussed by den Hollander et al. (2018), where the authors discuss the usefulness of video analysis and how greater context of ″how″ PIs lead to success is required to transfer knowledge in research into implementable change within elite sport. This begins to highlight the key limitations of match data and the requirement to investigate in further detail, such as sequence or phase play within the game to understand the relevance of PIs at this level.

## 2.3 Data Transformations and Methods

When investigating team sports, data transformation is often used to improve modelling, remove non-normality in data and give greater context to a team's actions in terms of the opposition. One such example is the use of relative data, that is, the value of one team's PIs in relation to the same PI for their opposition. In Bennett et al. (2019) a random forest method was used to predict match outcomes by using PIs in a relative form. For example, if Team A made 100 m and Team B made 200 m in a match, their relative PI values for metres made would be -100 m and +100 m respectively. Bennett et al. (2019) applied this methodology in the English Premiership, by using a season's worth of matches as well as in the Rugby World Cup (Bennett et al., 2020). This research sees the benefit of the use of relative statistics, where they improve prediction accuracy in modelling. Given PI data is often not normally distributed (Bishop & Barnes, 2013; Bunker & Spencer, 2021), this transformation may improve the distribution of data, which in turn improves modelling performance. This transformation also gives the PIs the context of the game at hand rather than raw metrics that do not consider what the opposition is doing within the game.

This technique has been repeated in the sub-elite game in the southern hemisphere (Mosey & Mitchell, 2020). Both studies highlight similar findings, with key relative PIs such as metres made, clean breaks and kicking from hand highlighted in both studies. However, Mosey and Mitchell (2020) did not report a significant difference in prediction efficiency between absolute and relative PIs, suggesting that this methodology may not extend into lower levels of rugby. Similar results were also reported in women's rugby (Scott et al., 2023). It may be that this method is less applicable in levels of rugby with larger score differences as discussed by Scott et al. (2023).

The use of relative data is not limited to rugby, with its earliest use recorded within football. Maher (1982) described the use of Poisson distribution to describe goal difference as a measure of the difference in attacking and defensive skills of two teams. This could be successfully used to predict match outcomes, although it struggled to decipher draws between teams. This concept was furthered by Dixon and Coles (1997), who modified the model to include reference to time, where more recent matches were weighted more heavily. This is a similar concept to that used by Bennett et al. (2019) and Mosey and Mitchell (2020), as it is known that match outcome (W/L) is simply a measure of points difference, similar to goal difference, and PIs being measures of attacking, defence and other themes of match performance.

Other data transformation techniques that can be considered are the use of time to interpret actions, namely measuring PIs per minute of match play rather than raw values (Lindsay et al., 2015). This transformation is more relevant when comparing positions or individual players to each other rather than full team performance, but is a prime example of the use of transformation to benefit contextual understanding of performance. This method has also been utilised within rugby league to understand ball-carrying ability but also to measure the collision load of the game (Naughton et al., 2020; Waldron et al., 2014), illustrating benefits when comparing players to each other. Furthermore, research within professional football has indicated that normalising PIs with the context of possession when analysing defensive capability, led to improved model performance and increased interpretability of modelling (Phatak et al., 2022). Given the invasive and evasive nature of rugby, this transformation may be implementable within different codes of rugby. This is an example of utilising the performance question to drive the transformation method.

Another consideration of modelling within rugby performance is model simplification. It is clear from the literature there are many PIs that can be considered in modelling (Colomer et al., 2020), however, when utilising research in practical environments, a large number of PIs does not give a clear message to practitioners of areas of application. Equally, another issue with large groups of PI as outputs is the potential of collinearity of metrics (Scott et al., 2023). Given this, a significant consideration for modelling PIs is the use of model simplification, which is yet to be researched within the rugby space. However, in other sports, many feature selection methods have been used to shrink the number of PIs in modelling (Rodrigues & Pinto, 2022; Sharma et al., 2021).

Equally, whilst not a feature selection method, principal components can also be utilised to simplify modelling and remove collinearity between PIs, as have been reported by Parmar et al. (2018) in rugby league. The PCA approach is beneficial as building components creates themes of areas of performance, however this can create some complexity in practical application. As components are made up of orthogonal transformations, monitoring PIs is difficult based on components alone rather than simple PIs themselves.

## 2.4 Understanding Matches at Different Levels

Whilst there is a significant amount of research into PIs at the match level, there is limited research within the literature analysing PIs at the sequence level, or equally the phase or team possession level. The research that exists is varied in terms of methodologies, outcomes and other key study design metrics.

Research that has been completed in this area varies in terms of the level of detail analysed and reported, with some authors utilising data at the sequence level (Bunker et al., 2021). Understanding matches at the sequence level is intuitive, given that sequences can be clearly separated by the ball going into and out of play. Sequence outcomes are also easy to quantify given the stoppage in active play.

Another method of analysing matches in greater detail is to investigate phases and possessions (Watson et al., 2020). This provides more play-by-play understanding, which may be more beneficial to coaching staff. However, phases are much shorter durations split between ruck breakdowns within sequences. Given the lack of stoppages in play, the outcomes of these may be less obvious and more varied. Possession also provides another opportunity for analysis, where the outcomes of possession can be reported and analysed. This can measure how effective a team are with ball in hand, which may be useful for practitioners. However, this may be less useful when analysing certain actions such as kicking, where possession ends immediately, but there may be interest in future events given a certain kick.

Other authors have also investigated try scoring passages (Coughlan et al., 2019; Marino et al., 2022), in order to understand what actions build up to scoring within matches. This is beneficial in interpreting attacking plays, but it is a limited dataset given try scoring passages form a small part of all passages of play during a single match. In fact, some matches may even be won without a try scored. Equally, this can be combined with the previous suggestion of the use of sequences, like was reported by Bunker et al. (2021), who compared scoring and non-scoring sequences.

Scoring passages are a dynamic event more well linked to other sports, where analysis has been completed on patterns of play rather than specifics like sequences or phases. Within other team sports such as football and handball, patterns of play can be analysed through investigating passing patterns (Caicedo-Parada et al., 2020; Korte & Lames, 2019). This analysis is useful in sports where the majority of actions are passes and collections. However, within rugby, there are on the ball events, including passing, kicks, and feeding the ball into a scrum or lineout, as well as off the ball events, such as tackling, rucking, scrummaging and mauling. Within rugby, there is also the added complexity of sequence, phases and possessions, which are potentially more strict than passages of other team sports. Given the diversity of actions in play, as well as the different measurements of time, it is clear that there is a requirement to take a unique approach to understand rugby beyond the match level.

Key methodology utilised differs across projects, with some authors modelling with methods such as random forest and neural networks, whilst others using methods such as clustering analysis via K-Modes or safe pattern pruning. Firstly, models such as random forest and neural networks are popular and repeated in other areas of performance analysis such as match level analysis (Bennett et al., 2019, 2020; Mosey & Mitchell, 2020), however, at a sequence or phase level, these models may not provide clear practical applications. For example, Watson et al. (2020) reports on 10 different models within the phase and possession analysis of rugby matches from both the club and international calendar using a combination of different modelling methods. However, the complexity of the models is difficult to interpret without further illustration provided for a selection of the models included. The scope of influencing practical decisions is significantly limited on both understanding of the outputs of the model and the ability to demonstrate this functionally to practitioners, this is a key disadvantage of using black box modelling styles.

Safe pattern pruning and K-Modes clustering are other methods utilised within this area in rugby, both using repeated patterns to investigate scoring outcomes (Bunker et al., 2021; Coughlan et al., 2019). These methods provide improved interpretation when the most common patterns are reported, meaning practitioners can easily understand the actions that lead to successful scoring outcomes. Markov chains provide a similar method of analysis, with similar outputs. However, as previously alluded to, sometimes winning strategies are singular moments of success rather than planned repeated successes. This is consistent when we consider what a small part of a full match scoring outcomes form, suggesting that pattern methods may not catch everything linked to success. There is definitely scope within this area, specifically in rugby and other sports, for simple descriptive statistics to form a basis of understanding prior to complex modelling.

Specifically in rugby, key results from analysis on sequences, phases and other patterns of play include the combinations of line breaks, set piece success, and regathered kicks being linked with scoring outcomes (Bunker et al., 2021; Coughlan et al., 2019; Marino et al., 2022), with spatial importance given to mauls and scrums in the attacking 22 m, as well as kicking in the centre of the field. Results also identified repeated rucks as an indicator of scoring outcomes (Bunker et al., 2021; Marino et al., 2022), suggesting repeated phase attack may be important. It is also reported that winning teams play more flexibly (Marino et al., 2022), which provides an interesting perspective on analysis. This is due to the fact that many methods utilised in detailed analysis of matches at this level aim to find repeated patterns within the data, which may be difficult where a successful outcome may be more varied than an unsuccessful outcome. Further detail is needed to truly understand what success is, and possibly greater context and descriptive statistics are needed to interpret success within rugby and other team sports.

## 2.5 Kicking Research and Other Skills Analysis

There has been significant research into PIs at the match level and limited related research aiming to interpret PIs over shorter periods such as sequences, phases or possessions. However, the next step to uncovering further insights, by increasing the detail of investigation, is analysing actions individually.

Kicking from hand is a key area of performance that has been highlighted as important as the match level, however, it lacks detailed analysis at the action level within the literature. The research that exists is varied and analysed from different perspectives such as injury profiling and lab simulations (Lazarczuk et al., 2020; Pavely et al., 2010). These studies provide some context of performance such as understanding the distribution of kicks types or interpretation of kick dynamics based on ball delivery, however the link to performance in game and how this can be improved is laboured as a performance outcome is not directly addressed. Studies have also investigated the analysis of kinematics and launch characteristics of kicking. Sinclair et al. (2017) analysed ten male rugby kickers to understand the three-dimensional kinematics of high velocity and accurate kicks. It was established that there were differences in kinematics between high-velocity kicks and accurate kicks. The theme of kinematics was also addressed by Holmes et al. (2006), who analysed ball launch characteristics utilising a high-speed camera on 14 elite kickers. Results identified that kickers could achieve velocities of 38.1 $ms^{-1}$, whilst they could only reach velocities of 18.3 $ms^{-1}$ when a spin pass was utilised. This analysis alludes to the probable link between the technical skills within the game and physical performance.

Moreover, the research on kicking that exists at the action level in rugby tends to favour the place kick over kicking from hand. Studies have focussed on the performance of place kicking, reporting success rates in the international game at 72%, and a decrease in successful placekicking when the distance and angle of the kick was increased (Quarrie & Hopkins, 2015). Authors have also investigated the biomechanical underpinnings of place kicking, utilising motion capture technology. Bezodis et al. (2018) reported that accurate place kickers were able to kick successfully from 33.3 m, and that this group has a moderately shallower swing plane inclination than the inaccurate group. Authors also identified that the accurate group placed their support foot moderately less far behind the ball than their inaccurate counterparts. Conversely, qualitative analysis has also been completed analysing the key constraints place kickers face through interviews with professional players and coaches (Pocock et al., 2020). This established the impact of environment and fatigue as key constraints as well as corroborated the impact of distance and angle to the goal posts as previously discussed (Quarrie & Hopkins, 2015). This is limited in improving in-game kicking performance, and more linked to individual place kicking.

Many authors have investigated tackle performance across different leagues of rugby. For example, K. M. van Rooyen (2012) analysed tackling performance across different international competitions. The dataset utilised in this research spanned 69 matches, with a mean of 159$\pm$40 tackles per match. This study identified that forwards tended to tackle more than backs, however, missed tackle rates were similar between both groups when corrected for group size. Authors also identified that more tackles were made in the Six Nations, compared to the Rugby World Cup and the Tri Nations (now known as the Rugby Championship).

The efficiency of tackles was also analysed by M. van Rooyen et al. (2014), in this case, focussing solely on tackles from a single Six Nations tournament. This study aimed to characterise and analyse ″effective tackles″ based on a set of definitions created by the authors themselves. This study found that losing teams made significantly more tackles, but despite an increased rate of ″less effective″ tackles made by losing teams, this difference between the two teams was not significant.

Hendricks et al. (2017) analysed tackles and ruck performances from the Six Nations and Championship competitions. This study included over 4000 tackles and 2900 ruck events to ascertain the technical determinants of these actions in international rugby. It established key relationships between front-on tackles and reduced the likelihood of offloading or tackle breaks, as well as the importance of the leg drive from the player being tackled, which can increase the chance of offloading. This study also identified that the ball carrier actively placing the ball as well as falling sideways were both determinants of maintaining ball possession at the ruck.

Line breaks have also been studied within the literature, as a measure of attacking performance. Studies have identified that the majority of line breaks were concentrated in the midfield area of the field as well as the majority being completed by backs (Diedrick & van Rooyen, 2011). Authors highlighted the occurrences of line breaks and analysed the greater context of how they happened, for example, line breaks were directed by additional passes and overlaps of attacking players. It was also identified that line breaks occurred when defensive lines were fast and when deception was used by attacking teams (den Hollander et al., 2016) and line-breaking players were twice as likely to score a try themselves than utilise a supporting player (Diedrick & van Rooyen, 2011). These studies are great examples of the utilisation of the greater action context given to the PIs, to understand how they are linked to success, providing thorough detail into both the field context of line breaks as well as differences from winners and losers.

Maintaining a focus on attacking strategies, Wheeler et al. (2010) reported insights into ″tackle break″ and their relationship to try scoring ability and team success. With methodology including Chi-Squared testing, it was highlighted that the ability to receive the ball at high speed and execute side-step evasion promoted tackle breaks, suggesting the link between physical and technical performance. This study is one of few to highlight this link, and the results provide an opportunity for the coaching staff to implement changes to influence these physical elements of the game.

Researchers have also investigated the link between PIs and physical performance measures. These studies take physical testing metrics and compare them with season-wide key PI values. Testing metrics include 10, 20 and 30 metre sprints, countermovement jump, isometric mid-thigh pull and many other metrics. These are completed at a single measurement session to give a stationary view on the current fitness of the player. There is benefit to understanding how physical metrics underpin the key PIs across the game, but there is a definite limitation within this study style.

Key findings highlight that sprint times over 10, 20 and 30 metres were weakly negatively associated with line breaks, metres advanced, tackle breaks and tries scored, suggesting that speed is a key area of importance for attacking play (Smart et al., 2011). It was also noted that there were relationships between on and around the ball activity rate, repeated sprint time and percentage body fat in forwards, and repeated sprint fatigue in backs. The authors recognise that the physical testing of these athletes was very uniform, which may in turn limit relationships between PIs and therefore impact the practical application of any results in strength and conditioning programming changes.

Similarly, strong relationships were identified between many of the testing metrics and PIs by Cunningham et al. (2018). This study included linear modelling to identify whether the changes in testing metrics required to cause a change in PIs are practically achievable (within 20% change). From this addition, it was established that only a small number of PIs can be altered from a practical perspective, including a change in drop jump or the Yo-Yo test to increase the number of tackles made and increase the count of being the first three players in the ruck in both attack and defence in forwards. In backs, a change in carries was associated with an achievable change in counter movement jump peak power output or improvement in the 5 metres sled hit time. This demonstrates that despite descriptive changes in the metrics, it may be difficult to implement these differences from a practitioner's perspective.

Many authors specialise in skills analysis of different skills within rugby and hence this research tends to span many different areas of the game (Wheeler & Sayers, 2009; Wheeler & Sayers, 2011; Wheeler et al., 2010, 2013). In contrast with their research into attacking strategies, defensive strategies have also been an area of interest for this research group. In one such study, ruck outcomes associated with defensive strategies were analysed, concluding that early counter ruck and jackals were effective at turning possession behind the advantage line (Wheeler et al., 2013). Another key area of interest from this research group is contact skills, with studies highlighting the importance of body position from both the ball carrier (Wheeler & Sayers, 2009) and the tackler (Wheeler & Sayers, 2011) and its link to evasive skills and tackle breaks.

A key theme across action analysis is the use of large datasets. In most studies, authors identify many actions from multiple matches to allow a broader understanding of the actions themselves, which may only happen a few times within a single match. For example, using kicks from multiple seasons (Lazarczuk et al., 2020) or tackle data from whole competitions (Hendricks et al., 2014), allowing authors to analyse from a broader perspective. Given this, these studies tend to employ primarily descriptive statistics, and also predominantly simple statistical testing such as the Chi-Squared test of association (den Hollander et al., 2016; Diedrick & van Rooyen, 2011; Wheeler et al., 2010).

## 2.6 Performance Frameworks and Holistic Approaches

When it comes to holistic approaches of performance, there is limited research within the area of rugby. Turner et al. (2019) developed a concept named Total Score of Athleticism (TSA), which utilised a team testing battery to quantify where an athlete is judged across relevant fitness capacities at the same time rather than their raw test scores alone. The TSA method determines the $z$-scores of athlete testing values, compared to their teammates, to interpret their strengths and weaknesses in different areas of the testing battery. This is then averaged across the testing battery to form the TSA score, a holistic overview of a player's physical testing measures. This is beneficial in two ways, firstly the use of the $z$-score of individual testing metrics allows practitioners to see areas where athletes may need to develop in comparison to their peers, and secondly, the TSA measure allows the analysis of a player as an individual across the board giving a full view of the fitness profiles. Turner et al. (2019), have identified a stable method of describing a player's overall testing fitness, however in application to rugby, this would not necessarily give a full view of an athlete's playing abilities, with technical and tactical capabilities being a practical part of the sport.

Within rugby, Bunker and Thabtah (2019) identified a need for a framework for utilising machine learning within match prediction. This study focussed on the use of artificial neural networks (ANNs) to approach match prediction. This framework highlights the domain and data understanding prior to any data extraction, preparation or model creation, which places importance on understanding the performance question and characteristics that may be unique to the sport. This section of the framework can be utilised across other methods within rugby. Equally, the authors highlight the importance of considering the granularity or level of data required to answer the objective of the performance question. Whilst this study itself may be specific to the use of ANNs in match prediction, the decision making process provides a framework that could be utilised in other modelling techniques and to other performance questions outside of match prediction.

Frameworks have also been created to develop certain skills such as tackling or other skills. The work of Hendricks et al. (2018) aimed to build a framework to develop and improve tackling skills over time, via scheduled training plans building up to competitive competition. This study, whilst not particularly relevant for elite teams, gives a glimpse into the concept of framework building within rugby. This study talks of the importance of the trade-off between skills learning and practical performance. This brings an interesting argument for team-based sports, that it is important to develop skills that can be transferred to the game, when players are likely under more physical stress and fatigue. Set piece and kicking plays are consistent parts of most games, and form a big part of match preparation in relation to tackling. The repetition of this reinforces skills so that they can be performed at a high intensity on match day (Hendricks et al., 2018). On the contrary to Turner et al. (2019), this study omits the relevance to the physical performance and its link to decision-making.

Calder and Durbach (2015) sought to combine the implications of results within the area of PIs with a holistic approach to understanding player performance. This methodology involved collecting a combination of frequency and percentage success metrics for various PIs and using them to rank player performance on an individual level. This analysis was run on separate player groups, with the authors addressing a key problem in complex sports like rugby, where many players' contributions do not necessarily directly link to scoring, so therefore may go unrecognised. However, the authors highlight another issue that they are unable to account for player interactions, for example, a scrum half may perform differently behind a strong pack than they would behind a weak pack. This research only analysed performance data across the match level, which may not give the depth of detail required to make systematic changes from a coaching perspective. However, this style of study may be more relevant for player selection or recruitment choices within a coaching team.

It is evident that there are varied methodologies across the literature in response to creating frameworks on sports performance, both within rugby and in more generic areas of physical performance. These frameworks all provide some basis to begin to understand how we analyse performance tactically from either a team level, an individual level and even from a physical performance view. However, to truly understand performance questions comprehensively across all of these levels, a combination of the frameworks discussed above would benefit both practitioners, in terms of performance question selection, and researchers, with data and methodology selection, as well as the dissemination of results to both groups.

## 2.7 Increasing Complexity in Research

Within sports performance, the complexity of the data available is increasing and hence so is the intricacy of research that can be completed on said data. A driver of complexity can be the increasing granularity available in data, both in terms of outcome and other variables available. This may be the granularity of the outcome metric, or the temporal and spatial metrics associated with the data analysed. Equally, the increase in both data availability and the speed at which it can be accessed has led to the growth of dataset size, which impacts both data preparation and methodologies utilised to infer knowledge.

Firstly, the outcome granularity is linked to the increased complexity of the data collected.

Traditionally, outcomes measured in performance research are categorical, including binary and multinomial variables. An example of this may be a binary win-loss outcome or a positive, neutral or negative sequence outcome. Increasing this granularity, the researcher may investigate a discrete outcome, such as number of tries or count of successful tackles. This leads to an increase in the complexity of analysis required to be applied to the data, moving from categorical to discrete variables of interest. Furthermore, this granularity may increase again to a continuous outcome. Authors may be interested in continuous metrics, such as ruck speed, kick distance or other measures of performance.

Secondly, there is also granularity in the temporal nature of our variable of interest. As highlighted previously in this literature review, predominantly within rugby, studies tend to focus on match level when it comes to temporal measurements. However, there is an opportunity to both increase and decrease this granularity within research studies. For example, instead of analysis across a match as a whole, research may investigate across sequences of a match to understand decision making in a match, or even just analyse actions individually. In terms of scale, a match level metric may well cover 80 minutes, whereas sequences are likely to span values from 30 seconds to a few minutes, with individual actions covering a few seconds at most. Inversely, there are opportunities to decrease granularity by analysing the variable of interest in rounds of a season, seasons themselves, or even across careers. It is important to note that the temporal measure relates to the level the researcher is interested in analysing, for example match, sequence, or action outcome, and not the dataset selection itself. To elaborate, one could collect data from an entire season, a few rounds or a single match, and analyse the data from the perspective of a sequence outcome. This would mean the granularity is still associated with the sequence level, regardless of the dataset size.

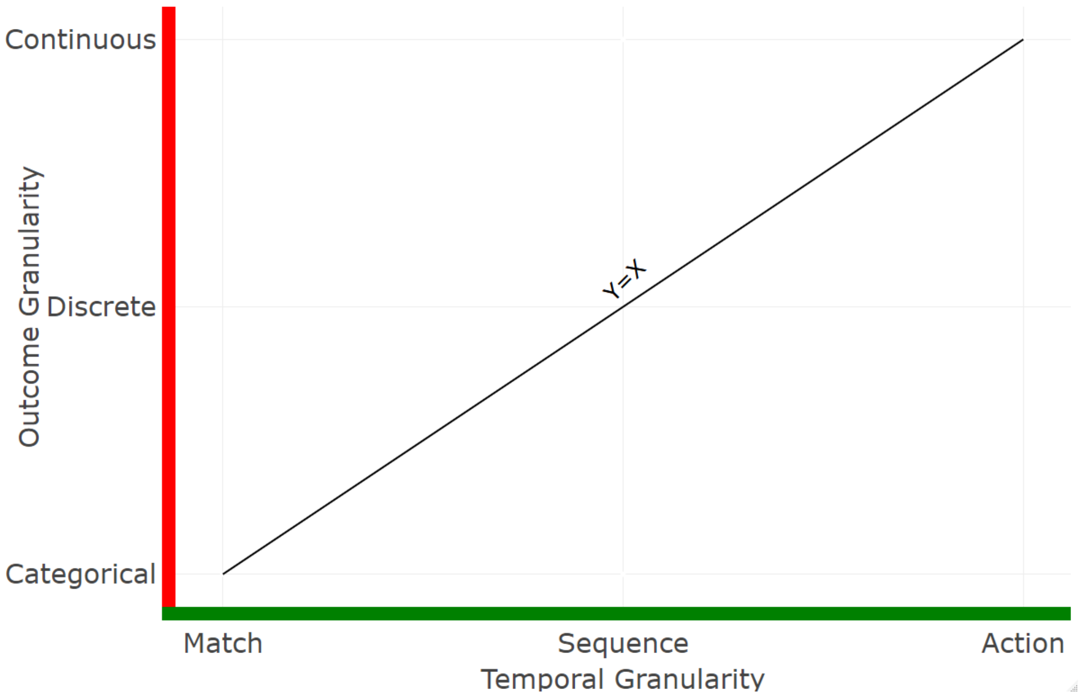



**Figure 2.1**
2D complexity space, with temporal granularity represented on the $x$-axis and outcome granularity represented on the $y$-axis. The $x$=$y$ line represents an equal increase in granularity across both axes.

When outcome and temporal granularity are combined, they can be placed on an $xy$-axis, with the $y$=$x$ line representing an increase in granularity in both equally. This is displayed in Figure 2.1. This figure displays a 2D visual of the complexity space, in which researchers do not necessarily need to follow the $y$=$x$ line to increase complexity, as granularity can also be increased in one axis at a time. Now, with the $xy$ plane conceptualised, the third spatial axis can be introduced.

The granularity of the spatial component of research is the third axis to be introduced. When analysing both the outcome and temporal measures, there is a greater context of where the actions take place available for analysis. In the simplest granularity, studies may not investigate what part of the field actions take place in, hence analysing the whole field regardless of position. Increasing the granularity, researchers may look to put context to the part of the field the action or sequences are situated in, such as a specific half of the field or even a specific zone of the field, such as the 22 m zone or other important areas.

Increasing this once more, studies may look to include the specific *xy* co-ordinate of actions to understand the positional influence on the metrics above. A key example of the latter would be research analysing the position of placekickers and success in kicking at goal (Quarrie & Hopkins, 2015). As with the previous axis, it is important to note that the spatial granularity is associated with the outcome of interest and not utilised as a data selection method.

Adding this third level of granularity to the previous figure (Figure 2.1) creates a 3D space visualising research complexity. In Figure 2.2, $x=y=z$ line now represents the increase in granularity in all three axes concurrently. As with the previous figure, this line does not necessarily represent the path a researcher may take to increase complexity within a project, as there may be multiple areas of interest in this space.

With difficulties in accessing, analysing, and interpreting spatial information, it means that many projects within rugby sit on the ″floor″ on this 3D space, with no reference to position on field given in analysis. Spatial research is becoming more popular with the improvement of data available to researchers and practitioners, predominantly data in XML formats. However, studies including this data type may have limitations regarding both practical interpretation and applications of this data. Select studies discussed in this literature review were plotted on this 3D space as an example of how this interpretation of the research space could be utilised in Figure 2.2.

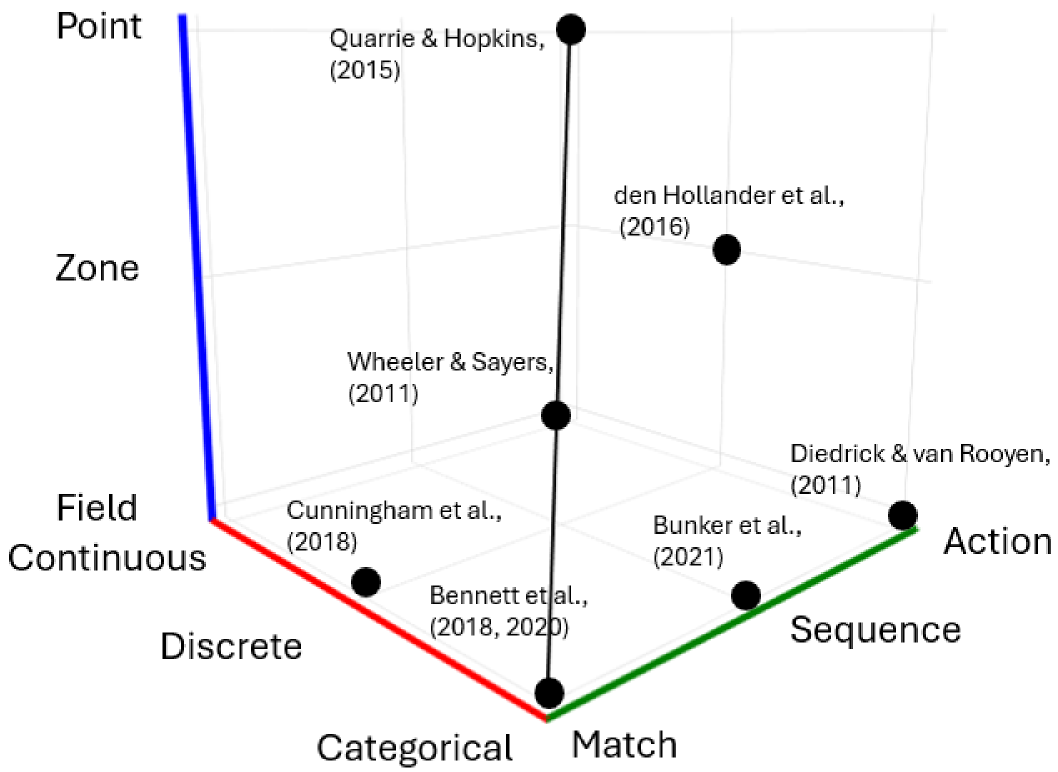



**Figure 2.2**
3D complexity space, with temporal granularity represented on the $x$-axis, outcome granularity represented on the $z$-axis and spatial granularity represented on the $z$-axis. The $x$=$y$=$z$ line represents an equal increase in granularity across all axes. Studies have been added with black markers, and the in-text citation has been utilised as a label.

This 3D complexity space can provide a decision-making process when starting a new project, and help support the project development by allowing the understanding of how to increase the complexity in a way that will benefit the project purpose. Increasing complexity need not be the direct aim but a supporting decision-making procedure to help decide where opportunities could lie in this space. For example, from mapping a performance question onto this space, researchers may be able to identify how they can increase the granularity of a certain axis in order to gain further insights from the data they have available. This space may even have optimal positioning for maximum insights for a given complexity. Moreover, plotting current literature on this space may begin to show what areas are most commonly researched, also identifying gaps in the literature.

As previously alluded to, the increase in granularity across the axes, and its linked increase in complexity is likely to impact dataset size, with both the number of variables available increasing and the number of observations. This impacts studies, both in terms of data extraction and processing, as well as modelling and statistical methods employed. This is a consideration for future studies and analysis plans, in terms of having appropriate personnel and equipment to cope with growing complexity.

## 2.8 Conclusion

Performance analysis is a significant area of research within rugby, with literature spanning multiple competitions globally. Despite this, there is a lack of research available for the United Rugby Championship and the equivalent predecessors such as the Pro14 and the Pro12 (Colomer et al., 2020). A key part of performance analysis is the investigation of PIs, that is actions that are utilised to define performance (M. D. Hughes & Bartlett, 2015).

These PIs are consistently researched at the match level, to analyse differences between winning and losing team performances. Studies frequently report the importance of attacking metrics, such as clean breaks and metres made (Bennett et al., 2019, 2020; Bishop & Barnes, 2013), as well as the importance of set piece, predominantly lineouts (Bishop & Barnes, 2013; A. Hughes et al., 2017). Kicking has also been identified recently as linked to successful performances (Bennett et al., 2019, 2020; A. Hughes et al., 2017; Mosey & Mitchell, 2020). The introduction of relative data has been reported in the literature as linked to improving model prediction of winning and losing match outcomes (Bennett et al., 2019, 2020). These studies report metrics in the context of the opposition, and suggest that making additional metres, breaks and kicks compared to the opposite team is linked to success.

Insights from successful performances across an entire match provide coaches with some understanding that can influence tactical decisions and playing styles, but to give greater context and assist with decision-making on field, further detail is needed. In the literature, studies have investigated more detailed aspects of play, such as sequences, possessions and phases to determine how PIs influence at these levels (Bunker et al., 2021; Coughlan et al., 2019; Marino et al., 2022; Watson et al., 2020). With results identifying that set piece, kick receipts and turnovers were linked to scoring opportunities.g opportunities.

The complexity of this analysis can be increased by analysing PIs at the action level, as has been reported in studies across different PIs. Tackling, rucks, line breaks and kicking are all actions that have been analysed at the action level with the aim of giving greater technical or physical context to the success of the PIs (den Hollander et al., 2016; Diedrick & van Rooyen, 2011; Hendricks et al., 2014; K. M. van Rooyen, 2012; Wheeler et al., 2010). These studies give greater context to both the field itself and also the physical link to these actions from a tactical and technical perspective.

Frameworks to understand performance have been utilised in general athlete performance, through TSA scores as reported by Turner et al. (2019). This system allows practitioners to interpret multiple elements of physical performance in an individual and compare both to their peers, but also themselves via $z$-scores. Equally, researchers have analysed frameworks to interpret performance indicators across players, allowing comparisons between personnel (Calder & Durbach, 2015). Frameworks have also been created to analyse specific technical skills such as tackling (Hendricks et al., 2018). However, there is a lack of literature analysing a holistic view of performance, from a team level down to an individual level.

It is clear with the increase in data availability, including additional metrics and observations, that the questions that can be asked of the data will change, possibly leading to increasing complexity in many different ways. Understanding this increasing complexity and how it can be utilised to plan research projects and to grow insights at many different levels, is key to allowing research to influence practice.

In conclusion, there is a requirement to not only understand performance within the URC from a match level but also a more detailed level including sequences and actions. It is vital to co-ordinate findings between each level to build a holistic view of performance, where implementable change can be made from coaches and other performance staff. Analysing this brings complexity, and understanding how to traverse this is key to building insights as the complexity of the data available increases.

# 3 General Methods

## 3.1 Introduction

This chapter outlines the key methodological approaches for data selection, processing, and analysis utilised within this thesis. This includes the discussion of participants and ethical approval required for the studies completed, and the reliability and validity of the data collected from the data provider, OPTA. Given the similarities in the datasets used across studies, this chapter allows the discussion of key data selection decisions as well as the explanation of the corresponding language utilised to describe the data and processing steps completed on the data. Finally, the description of how statistical analysis was completed in this thesis is also described within this chapter.

## 3.2 Participants and Ethics

The data utilised within this thesis was collected from OPTA and contains action details from matches across the URC between the 2017/18 and 2021/22 seasons. This includes player and team actions throughout the competition. These are professional players representing the 16 clubs involved within the competition, and consent for data collection is agreed privately between OPTA, the clubs and the competition organisers.

Ethical approval was obtained from Swansea University, College of Engineering Research Ethics and Governance, under ethics application number GS310821 for the Chapter 4, concerning match performance indicators. For Chapters 5, 6 and 7 regarding kicking, ethical approval was obtained separately under ethics application number GS271022. Both letters confirming ethical approval can be found in Appendix A.1.

## 3.3 Data Reliability and Validity

OPTA is a global data analytics business that collects data across all major sports, providing statistics and graphics to major broadcasters, websites, news outlets and sport fantasy leagues (Stats Perform, n.d.). OPTA also provide data to professional clubs across many different sports, via a paid subscription service.

Data is collected live from every match, by live collection teams. Each team contains six members and is overseen by a supervisor. One analyst records all match events for Team A, whilst a second analyst records all events for Team B. A location analyst tracks all $xy$ coordinates of the on-ball events on the field and inputs them into a data file. The timeline and OOA analysts both log and verify the timestamped actions during the match. A supervisor oversees the collection process, and a quality control and integrity check is completed post match before data is live to customers on the subscription service. A summary of roles can be found in Figure 3.1.

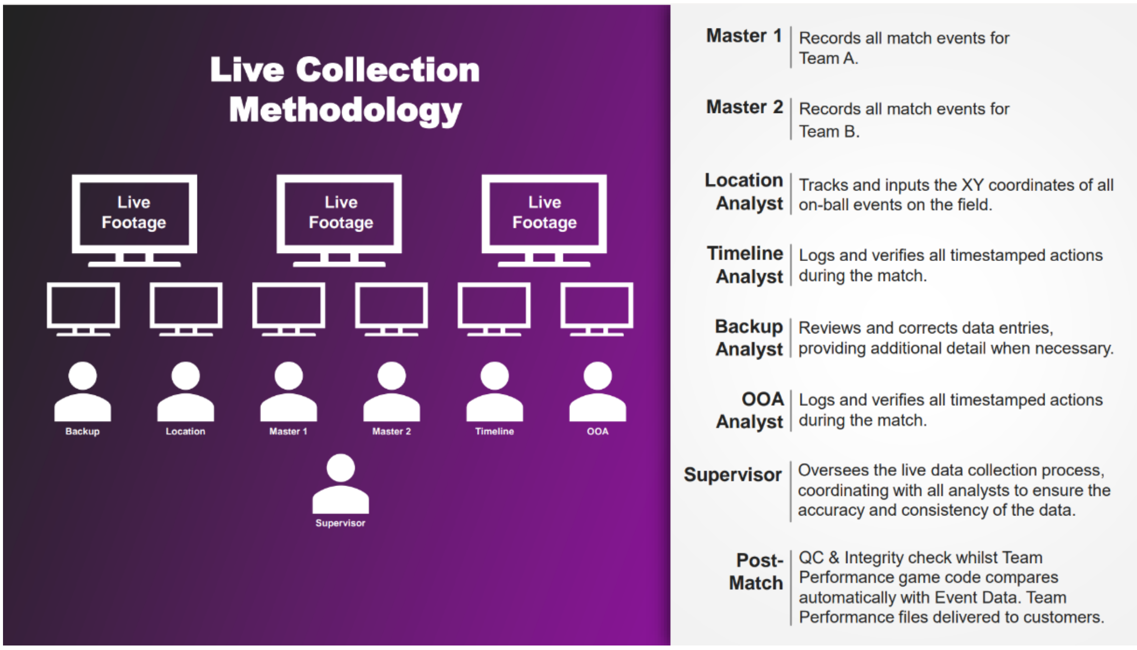



**Figure 3.1**
A visual representation of OPTA Live Collection Methodology, including roles of each member of staff involved on match day. This image was provided by OPTA. (Stats Perform, n.d.)

A short validity and reliability study was completed to determine the accuracy and consistency of the kick action data provided by OPTA. A random sample of 50 of each of the seven kick types was created ($n = 350$ in total). The timestamps were then identified and each kick was verified by a single reviewer from match footage. OPTA provided at least one angle of footage on their website (primarily the TV footage angle), however, some games featured a second wide angle. The kick type, outcome and starting and ending $xy$ coordinates were recorded for each kick and compared to OPTA's original values.

Outliers were removed where values were significantly different to the values provided by OPTA, this occurred where kicks were more than 10 m different compared to their coordinates recorded by OPTA. This included 6 kicks, and in this case, kick type and outcome were incorrect, suggesting an error made in coding by the original operator.

The study established an accuracy rate of 91% in kick type, within this all touch and box kicks were correctly identified. The discrepancy rate of each other kick type was as follows: 6% of bomb kicks, 10% of chip kicks, 18% of cross pitch kicks, 12% of low kicks and 14% of territorial kicks.

It was also identified that kick outcome had a 92% accuracy, including a 100% accuracy rate for outcomes including charged down kicks, in goal kick, pressure in touch kicks and try kicks. The discrepancy rate for other outcomes was between 3-12%.

Within the $xy$ starting coordinates, 90% and 83% were within 2 m of the original OPTA position respectively. It was also determined that 86% and 87% of the end $xy$ coordinates were within 2 m of the original OPTA coordinates. The error rate was consistent across the full area of the field for each coordinate set, with no significant clustering of concentration observed in any specific area.

## 3.4 Data Collection Procedures

Before accessing data from OPTA, factors were considered to ensure an appropriate size and depth of data were acquired. This included limiting the number of seasons that were considered for analysis. The last significant change occurred in 2017 when many laws around the scrum and ruck were amended (World-Rugby, 2017b). Due to this, the seasons initially chosen for analysis were 2017/18, 2018/19, 2019/20 and 2020/21. The first ten rounds of the 2021/22 season were used to evaluate the prediction of any modelling completed on the 2020/21 season in Chapter 4. The latest law changes began in 2021/22 season (World-Rugby, 2021). This does not affect the dataset used for initial modelling in Chapter 4, but does impact the data used for prediction, and the data utilised in consequential chapters.

The data used included all teams who have played any matches within the United Rugby Championship, and its predecessors, such as the PRO14 and the PRO12. This included 12 regional teams from the northern hemisphere, including four from Ireland, four from Wales, two from Italy, and two from Scotland. The southern hemisphere was previously represented within this structure via South African teams: the Cheetahs and the Kings. These teams were unable to compete in the 2020/21 season due to travel and financial issues caused by the COVID-19 pandemic (Reid, 2020) leading to both teams leaving the league altogether. In the 2021/22 season, four teams from South Africa were added: the Bulls, the Lions, the Sharks and the Stormers (BBC, 2021).

A group of 26 PIs were chosen to align with key areas of the game, namely attack, defence, rucks and turnovers, set piece, and penalties and infringements. These 26 were chosen from the team reports that were available to teams in OPTA. These 26 PIs allow the chapter to analyse a balance of PIs across different areas of the game, including attack, defence and discipline. While no study has used identical variables, many of the reported variables have been included across studies in this area (Bennett et al., 2019, 2020; Bishop & Barnes, 2013; A. Hughes et al., 2017). As these reports are available from OPTA, it is likely that practitioners will be aware of them and possibly follow a similar variable set in their own data collection and analysis. Home and Away markers were also included in the PI set, as there is a tendency that teams will obtain favourable results when they play matches at home (Vaz et al., 2012). A full list of definitions of performance indicators by group is presented in Appendix A.2.

All data was downloaded from OPTA, via www.optaprorugby.com. For analysis pertaining to Chapter 4, CSV files were downloaded for each season described above, containing the PIs set for each match within that season. For Chapters 5, 6 and 7, individual match files were utilised to gain further context for each kicking action. Given the success of prediction within Chapter 4 on 2021/22 season, and the results from Chapter 4 identifying differences between seasons, only the 2021/22 season was utilised in the subsequent chapters. Each match file was available to download individually in a time-coded XML format. Using a combination of Javascript and the R Package RSelenium (R-Open-Science, n.d.), a web scraping loop was written to download the entire 2021/22 season via Firefox automatically. The data downloaded was the saved into a folder ready for data manipulation in R.

## 3.5 Data Processing and Analysis

### 3.5.1 CSV Processing

The CSV files were loaded into R for processing and further metric calculation prior to formal analysis. Points-based indicators, namely tries, penalty goals, conversions, drop goals and penalty tries were used to calculate the related score for each team during the match, however, it was noted that penalty tries were captured twice, once in tries and once in penalty tries. A function was used to correct for this in calculations of the new variable, points for (PF), to denote the points scored by a team during a match. The scores by match were then aggregated and matched so that a secondary variable, points against (PA), could be created to denote points conceded by a team during a match. Points difference (PD) was also created to denote points difference between both match teams. The match outcome was then recorded based on the PD, indicating which team had won, (W) and which had lost (L).

Match names were checked to identify the leading team (traditionally the home team in rugby match naming format) and matched to the team the statistics were from. This was used to code whether the match was played Home or Away for the team in question.

The full variable set used can be found in Table 3.1.

**Table 3.1**
Breakdown of performance indicators ($n = 27$) utilised in the analysis of the Chapter 4, split into groups by theme.

| Group | Performance Indicators Included |
|---|---|
| Attack | Carries |
| | Metres Made |
| | Defenders Beaten |
| | Offloads |
| | Passes |
| | Kicks from Hand |
| | Clean Breaks |
| Defence, Rucks and Turnovers | Tackles |
| | Missed Tackles |
| | Turnovers Won |
| | Turnovers Conceded |
| | Rucks Won |
| | Rucks Lost |
| Set Piece | Lineouts Won |
| | Lineouts Lost |
| | Scrums Won |
| | Scrum Lost |
| Penalties and Infringements | Penalties Conceded |
| | Free Kicks |
| | Scrum Penalties |
| | Lineout Penalties |
| | Tackle/Ruck/Maul Penalties |
| | General Play Penalties |
| | Control Penalties |
| Cards | Yellow Card |
| | Red Cards |
| Other | Home or Away Status |

Furthermore, as previous research (Bennett et al 2018, 2020) used relative statistics to analyse rugby datasets, a similar dataset was created for this data. For example, if Team A made 300 m and Team B made 400 m, the relative data would be -100 m and 100 m respectively. Relative scores were calculated for all numerical variables within the dataset. From now on in this thesis, isolated data will designate the data without any context of the opposition team performance and relative data will designate the relative data as calculated above. Nomenclature will be used to identify variables belonging to each group as follows,

$\text{PI}_I$ will indicate a PI in its isolated form and $\text{PI}_R$ will indicate a PI in its relative form. For example, $\text{Carries}_I$ is related to isolated carries and $\text{Carries}_R$ is related to relative carries.

### 3.5.2 XML Processing

The XML files were also loaded into R for processing and further metric calculation prior to formal analysis.

Files were loaded into R and combined to create a large database. This was then transformed into a large data frame, and definitions supplied by OPTA were applied to turn the numeric identifiers into their text equivalents. This included all action definitions, additional action descriptions and player and team identification.

Within the XML files' structure, there were 3 files involved in the match data. The first was the Match Data file, which included all time-coded actions of the match from both teams involved. This was the largest dataset of the three and will be the focus of the analysis in this thesis. Within this file, there were 25 variables available for each action that took place in a match. They are defined in Table 3.2. The second file was the Team Data file, this included details of the players in each team involved in the match. This specified players' name and identification number, team name and identification number, playing position, shirt number and their minutes played. The final file was the Fixture Data, this file includes all the meta-data related to the match overall, including the date of the match, the fixture week, fixture ID, the home team name and identification number, the away team name and identification number, the full-time scores for both teams, the referee name and identification number, and the lead time.

**Table 3.2**
XML variables and definitions available for each action of a match event file available for each fixture in the United Rugby Championship.

| Variable | Definition |
|---|---|
| FXID | Match Identification Number |
| PLID | Player Identification Number |
| Team ID | Team Identification Number |
| Timestamp | Start clock time of an event, not stopped for time stoppages in play. (s) |
| End Timestamp | End clock time of an event, not stopped for time stoppages in play. (s) |
| Match Time | Match time of an event, including time stoppages in play. (MM:SS) |
| Period | The half in which the action took place, 1 refers to the first half and 2 refers to the second half. |
| X Co-ordinate | The starting $x$ coordinate of the action, the $x$-axis runs along the sideline of the field of play. |
| Y Co-ordinate | The starting $y$ coordinate of the action, the $y$-axis runs across of the field of play. |
| X Co-ordinate End | The ending $x$ coordinate of the action, the $x$-axis runs along the sideline of the field of play. |
| Y Co-ordinate End | The ending $y$ coordinate of the action, the $y$-axis runs across the field of play. |
| Action | The action that took place. |
| Action Type | A description of the type of action that took place. |
| Action Result | The outcome of the action that took place. |
| Qualifier 3 | Additional description of the action, its type or outcome. |
| Qualifier 4 | Additional description of the action, its type or outcome. |
| Qualifier 5 | Additional description of the action, its type or outcome. |
| Metres | The metres gained over the advantage line by the action. |
| Play Number | The phase number the action took place in. |
| Set Number | The possession number within the game. |
| Sequence ID | The sequence the actions took place in. A sequence begins when the ball goes into play and continues until it goes out of play again. There may be multiple plays/phases in one sequence. |
| Player Advantage | How many additional players a team have on the field at the time the action took place, this may be due to cards or injuries. |
| Score Advantage | How many more or fewer points does the team completing the action have, compared to their opposition. |

The actions and their related descriptive columns are key parts of analysis within this thesis. This dataset features all actions that take place within a match of rugby, both in defence and in attack. There are 25 unique actions in this dataset, with 155 descriptions of action types, and 98 descriptions of action results. There are also three further qualifiers of the data, with 45, 25 and 26 unique descriptions respectively. It should be noted that not all actions have a full breadth of descriptors as described above.

A sequence is a set of contiguous actions, starting when the ball goes into play and ending when it comes out of play or the whistle is blown by the referee. Within each sequence, a sequence identifier action existed, which gave the information of how, at what time, and where on the field the sequence began and ended. This indicator was moved to the end of the sequence to improve the interpretation and application of any sequential analysis. Throughout the dataset, a possession indicator was used similarly to mark the end of a certain team's possession.

Within the dataset, certain actions were removed to improve the interpretation of sequences. Players leaving and entering the field were removed, given this solely happened at the end of a sequence. Referee reviews were removed as traditionally they are completed off the clock, hence a sequence would have to end for this to happen. Identifiers of the clock going on and off were also removed, as these would also happen at the end of a sequence. These actions all happen when the ball is out of play, hence do not contribute to in-game kicking performance.

Within original scrum actions, each individual player was attributed an action when they were included in a scrum, as well as an overall team action. To simplify this, only the team scrum action was maintained within the dataset.

Sequences described as ending with an outcome of ″Other″, any sequence that included a penalty goal kick and one sequence with a known error were removed. Based on the values removed in each category, many goal kicks were categorised as ″Other″ and hence removed in that step. As this thesis aimed to interpret sequence outcome, it is impractical to include sequences with no sequence outcome recorded, nor do goal kick sequences add to the understanding of kicking performance as a goal kick is a prescribed action completed by a single player in isolation. Goal kicks are not considered a kick from hand, as they are kicked from a tee and not during team play of the game, hence are not included in kicking from hand statistics. Furthermore, any sequence with less than four actions was identified and manually analysed. This identified that all sequences with less than four actions in this dataset were either penalty kicks to touch, penalty taps that were then kicked immediately out of play or restart kick errors. Given the size and known interpretation of these sequences, they were removed from the dataset as they were unlikely to contribute to the interpretation of kicking from hand. A flowchart of the data selection process can be viewed in Figure 3.2.

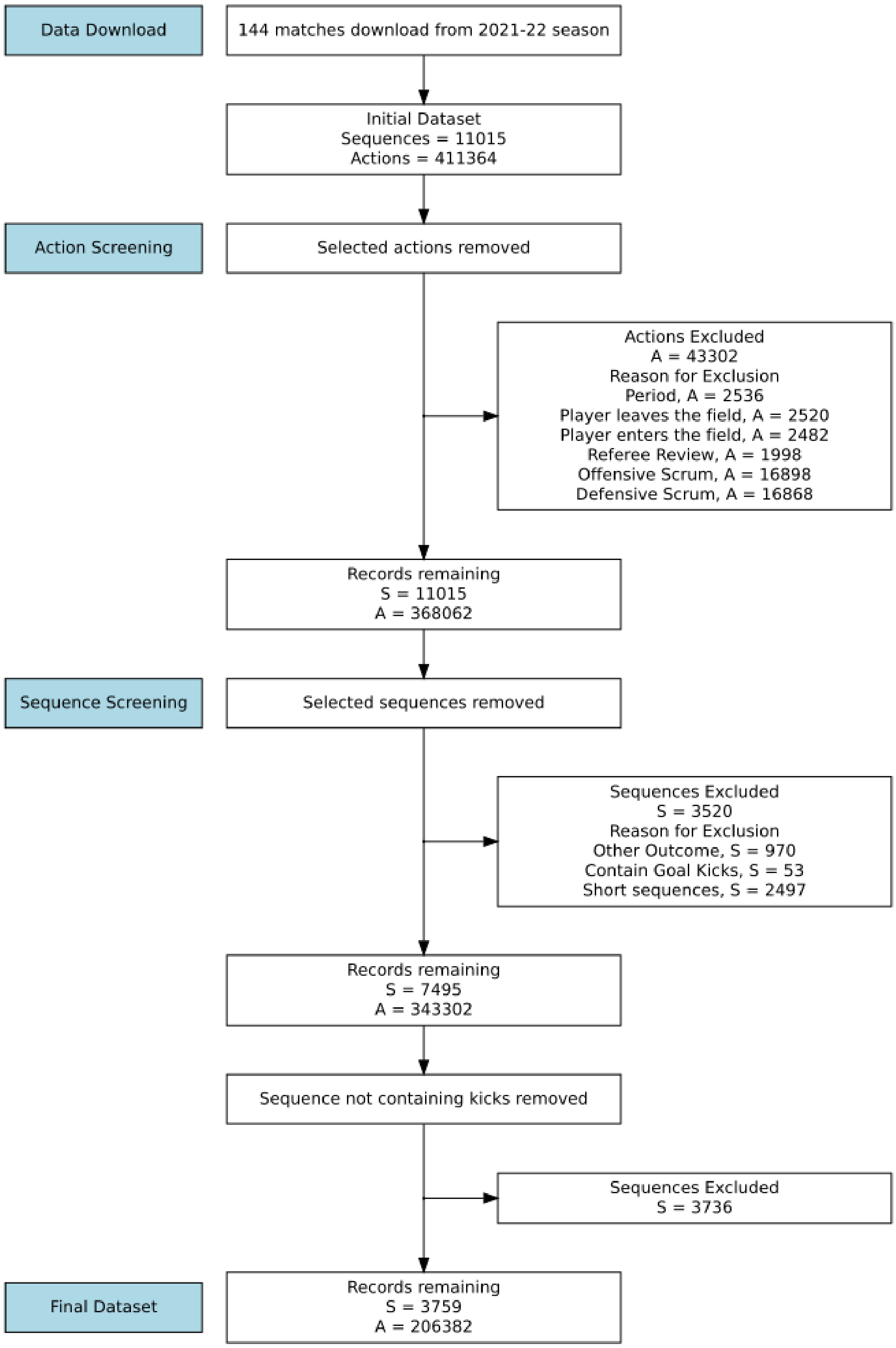



**Figure 3.2**
Flow chart of data processing for XML data, including sequences and actions left after each screening and reasons for any exclusions.

Restart kicks were not included in this analysis as they are required to initiate a new sequence of play under the laws of rugby (World-Rugby, 2022), rather than tactical kicking choice within an already commenced sequence. Similarly, drop goal kicks were also excluded as, although it may take a tactical decision to get into position to complete a drop goal, the expected outcome is known and directly linked to points. Both kick types are coded separately to kicks from hand, hence were not included in the kicking from hand statistics.

Many of the sequences ending in a kick error had *xy* end coordinates of the end of the kick rather than the *xy* coordinates of where it was taken. When a kick error occurs, the lineout at the beginning of the next sequence takes place at the position of the kicker rather than the endpoint of the kick. Without correction, this error would incorrectly inflate any territorial gain in future calculations. This was corrected in all kick error sequences by replacing the *xy* end coordinates with the position of the kicker.

Sequences were split into three groups based on their outcomes: positive, neutral and negative. Positive outcomes were situations where a team has either scored a try, won a penalty or gained possession of the ball via a scrum or a lineout for the next sequence. Negative outcomes included turning over the ball, conceding a penalty or try, or making a kick error. The remaining outcomes were classified as neutral, including end of play, kick in goal, kick in play (when a mark is called by a player) and kick out of play. For the kick in goal, kick in play and kick out of play outcomes, teams may benefit from a territorial advantage but they also lose possession of the ball and may have missed out on a scoring opportunity when this possession is lost. Due to this, the outcome for this is considered neutral. One situation where this is not the case is when a team kicks the ball into their opposition 22 m zone, from their own half. From the 50:22 rule, the kicking team will gain possession of the ball at the lineout, therefore this has been included as a positive outcome via the ″Own Lineout″ sequence outcome. All outcomes are given in the context of the team in possession at the end of the sequence. This methodology of categorising outcomes was discussed with two practitioners within Ospreys, and the groupings are listed in Table 3.3.

**Table 3.3**
Sequence outcomes by group for all sequences remaining after data processing, split into positive, neutral and negative outcome groups.

| Positive | Neutral | Negative |
|---|---|---|
| Drop Goal | End of Play | Kick Error |
| Own Lineout | Kick in Goal | Penalty Conceded |
| Penalty Won | Kick in Play | Turnover Scrum |
| Scrum | Kick Out of Play | |
| Try | | |

With the transformed dataset, the team in possession at the end of the sequence was identified, as this is the team to which the sequence outcomes are attributed. Sequences that did not have a possession indicator at the end of the sequence were manually investigated to find the correct team in possession ($n$ =222). Furthermore, the sequence outcome for the kicking team was also added to each kick throughout the dataset.

Total kicks per sequence were calculated as a sum of both teams' kicks, and then kicks per team were also calculated. This was then used to calculate the relative kicks by sequence. Relative kicks indicate how many kicks a team has made in comparison to their opposition, for example, if Team A made two kicks in one sequence and Team B made one, the relative kicks for each team would be +1 and -1 respectively. The nomenclature of +1 and -1 kick was used throughout this thesis to denote one additional kick or one less kick than the opposition respectively. The relative kicks were given in the context of the team in possession at the end of the sequence, as this is how the sequence outcomes were attributed. This is distinct to relative kicks per match, which are relativised between winning and losing teams for the match overall. The

Within each sequence, the first kick was identified and attributed to its respective team. For each kick, it was identified whether the first kick was taken by the team in possession at the end of the sequence or not. This sequence dataset was split into two groups, a group of all sequences and a smaller group of only sequences containing kicks. Within this thesis, only the latter were investigated as the aim is to understand kicking at the sequence level. These sequences will be referred to as ″kicking sequences″.

### 3.5.3 Kick Groupings

In later chapters, namely Chapters 5, 6 and 7, kicks are grouped by different measures including kick type, kick zone and kick outcome. This section aims to summarise all measures and the definitions of each type, zone and outcome.

#### 3.5.3.1 Kick Types

OPTA reports seven named kick types within its XML structured files. These kicks were bomb, box, chip, cross pitch, low, territorial and touch kick. These are described in Table 3.4 as per OPTA definitions.

**Table 3.4**
Kick types and descriptions for each kick type given by OPTA.

| Kick Type | Kick Description |
|---|---|
| Bomb | The kick was struck high in the air, in order to give the offensive team time to put pressure on the receiver or claim the kick themselves. |
| Box | The kick has been taken directly by a player collecting the ball from the back of a ruck, maul, scrum or lineout. |
| Chip | A short-weighted kick, usually over the top of the defensive line, for attacking players to run onto. |
| Cross Pitch | The kick has been struck to the opposite side of the pitch to the kicker, in a lateral direction. |
| Low | The kick has been struck so that its trajectory is close to the ground, for attacking players to run onto. |
| Territorial | The ball has been kicked with the aim of gaining field position. |
| Touch | The kick has been struck with the intention of it going over the touchlines during a penalty kick or to end play. |

#### 3.5.3.2 Kick Zones

To understand the locations at which kick took place, the field was separated into five different sections, which will be referred to as ″zones″ in this thesis. Zones were colour-coded as follows: Red, Silver, Gold, Blue and Green. Kicks were categorised into these zones based on their position on the field. Each zone was defined as follows:

**Table 3.5**
Field zones names, areas and descriptions.

| Zone Name | Zone Area | Zone Description |
|---|---|---|
| Red | 78 m to 110 m | From the opposition team's 22 m to their own dead ball line. |
| Silver | 60 m to 78 m | From the opposition team's 10 m to their 22 m. |
| Gold | 40 m to 60 m | From a team's own 10 m line to their opposition team's 10 m line. |
| Blue | 22 m to 40 m | From a team's own 22 m line to their own 10 m line. |
| Green | -10 m to 22 m | From behind a team's own dead ball line to their own 22 m line. |

A visual representation of this field can be found in Figure 3.3

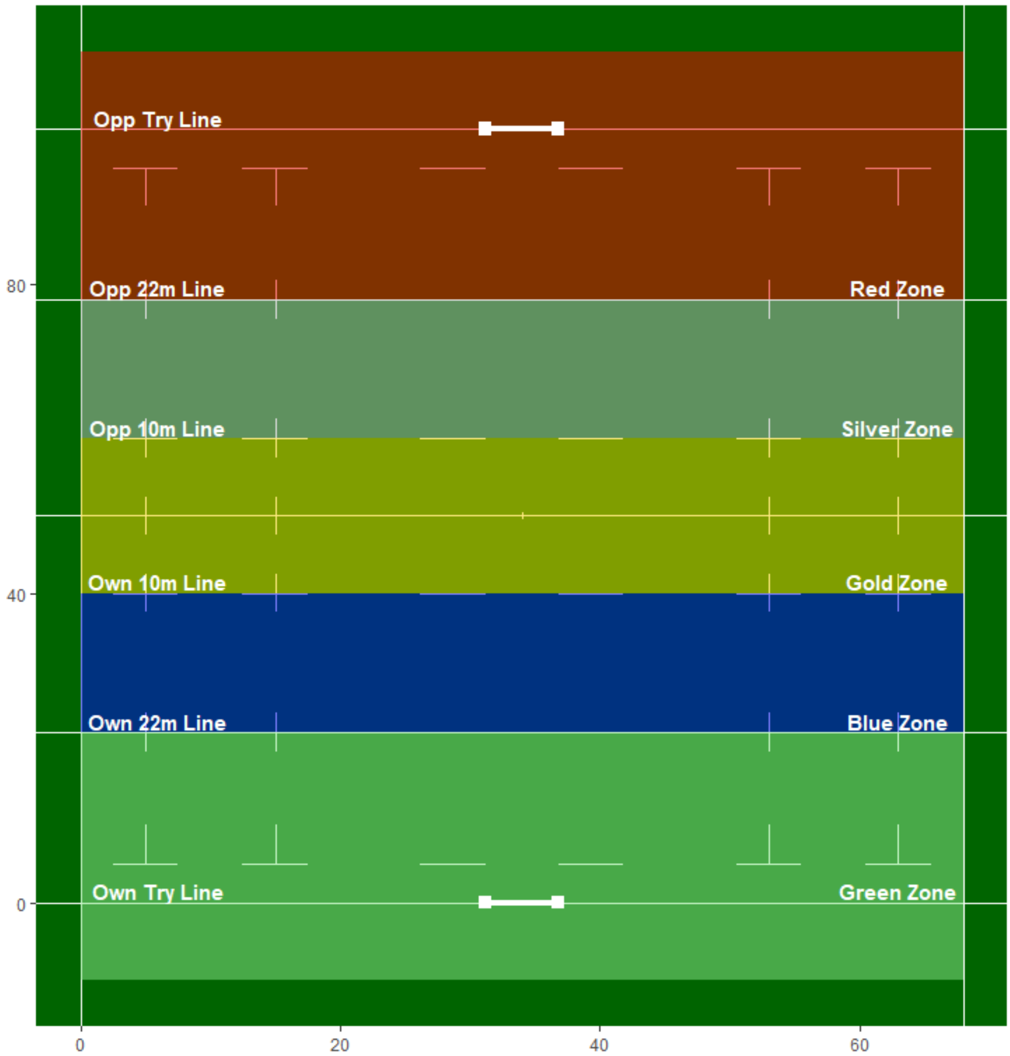



**Figure 3.3**
A visual representation of the field zones on a standard Rugby Union field. A team's own 10 m, 22 m and try line are annotated, as well as the opposition's 10 m, 22 m and try line. Vertical and horizontal 5 m lines are denoted by dotted lines, as is the vertical 15 m line. The zones of the field are also annotated. The bold boxes and lines represent the posts.

These zones are given in descending order from the opposition's try line to a team's own try line. The red zone is the only zone consistently utilised in literature to identify the area between the opposition 22 m and try line (Burt et al., 2015; M. T. Hughes et al., 2012). This has been extended to include inside the try zone and the dead ball line, allowing the analysis of actions within the try area itself. This system of zones has an additional field area compared to previous studies (K. M. van Rooyen & Noakes, 2006), with the area between the two teams' 10 m lines as a separate zone rather than part of the blue and silver zones. This area identifies the centre 20 metres of the field separately. Analysing this area may help define obvious offensive and defensive approaches observed in the surrounding zones, whilst also giving context to what happens in the central, often ambiguous, area of the field.

#### 3.5.3.3 Outcome Groupings

Kicks were segregated into six groups based on six possible outcomes directly after the kick. The first kick, first pass and first tackle made immediately after each kick were noted and then used to group each kick. An extended definition of each group can be found in the Table 3.6.

**Table 3.6**
Grouping definition based on the next action following the collection of the kick.

| Group Number | Group Description | Definition |
|---|---|---|
| 1 | Tackle First | The player who collected the ball was tackled before making a pass or kick. |
| 2 | Pass First | The player who collected the ball made a pass before being tackled. |
| 3 | Kick First | The player who collected the ball was able to kick the ball before being tackled. |
| 4 | Pass and Kick First | The player who collected the ball was able to pass the ball before being tackled, and a teammate was able to kick the ball away. |
| 5 | Try Scored | The player who collected the ball scored a try before another action took place. |
| 6 | No Further Action | The collecting player makes no pass or kick and is not tackled, either due to knocking on the ball and play continuing or the whistle being blown before any further actions are taken. This may be due to an error or penalty made in the collection or to stop play based on an earlier advantage, or if the catching player goes into touch or calls the mark from the ball. |

## 3.6 Statistical Analysis

All statistical testing was completed in R Studio. A significance level of 5% was used throughout this thesis. Bonferroni's correction was the preferred method of accounting for multiple testing within this thesis. All statistical methods are described in each study chapter.

## 3.7 Conclusion

This chapter outlined the methodological framework of the studies included as part of this thesis, including data selection, processing and analysis, as well as data validity, reliability and statistical analysis. This chapter identified reliability in OPTA data, with 91% and 92% accuracy in kick type and outcome. It was also identified that between 83-90% of coordinates were within 2 m of the original OPTA recorded coordinates. Consideration must be given to the fact the reliability study was completed by a single reviewer due to data privacy guidelines from OPTA and ethical approval, which add potential bias in comparison to the original data collection methods by OPTA, which comprised multiple operators in each game. This chapter also discussed data selection for the thesis, including the exclusion of data from before 2017, when a law change took place, and the exclusion of different actions and sequences within the datasets to improve and simplify analysis.

Key processing and analysis that was completed was also summarised, including zone and outcome groupings of kicks and the calculation of variables such as points difference and relative data. Finally, a summary of how statistical analysis was completed within this thesis was also included.

# 4 What does success look like in the United Rugby Championship?

The study that comprises Chapter 4 has been published in the Journal of Science and Medicine in Sport. Chapter 4 is similar to the published version, with additional exploratory analysis including the justification of data selection.

Reference: Scott, G. A., Bezodis, N., Waldron, M., Bennett, M., Church, S., Kilduff, L. P., & Brown, M. R. (2023). Performance indicators associated with match outcome within the United Rugby Championship. Journal of Science and Medicine in Sport, 26(1), 63-68. https://doi.org/10.1016/j.jsams.2022.11.006

## 4.1 Abstract

**Background** Data analytics techniques have been utilised to determine performance indicators associated with match outcome in rugby. Typically, these studies report many key performance indicators, however, utilising a high number of these metrics can impede actionable interventions by practitioners. No key research has investigated variable selection methods to build and validate simplified models capable of predicting successful performances. Equally, there has also been no evidence of research within the United Rugby Championship.

**Aims** The aim of this chapter was to understand key performance indicators associated with match outcome in the United Rugby Championship.

**Methods** Twenty-seven performance indicators were selected from 96 matches (2020–21 United Rugby Championship). Random forest classification was completed on isolated and relative datasets, using a binary match outcome (win/lose). Maximum relevance and minimum redundancy performance indicator selection was utilised to reduce models. Models were tested on 53 matches from the 2021–22 season to ascertain prediction accuracy.

**Results** Within the 2020–21 datasets, the full models correctly classified 83% (77%, 88%) of match performances for the relative dataset and 64% (56%, 70%) for isolated data, the

equivalent reduced models classified 85% (79%, 90%) and 66% (58%, 72%) respectively. The reduced relative model successfully predicted 90% of match performances in the 21–22 season, highlighting that five performance indicators were significant: kicks from hand, metres made, clean breaks, turnovers conceded and scrum penalties.

**Conclusion** Relative performance indicators were more effective in predicting match outcomes than isolated data. Reducing features used in random forest classification did not degrade prediction accuracy, whilst also simplifying interpretation for practitioners. Increased kicks from hand, metres made, and clean breaks compared to the opposition, as well as fewer scrum penalties and turnovers conceded were all indicators of winning match outcomes within the United Rugby Championship.

## 4.2 Introduction

When quantifying success within rugby, understanding performance indicators (PIs) within matches can be useful in investigating what underpins winning and losing performances. Performance indicators have been studied previously in many areas of rugby including international and club levels around the world (Colomer et al., 2020). Prior research has focused primarily on international rugby (M. T. Hughes et al., 2012), the English Premiership (Bennett et al., 2019) and Super 12 (Coughlan et al., 2019) with the majority of research on performance indicators without the context of their opposition (Colomer et al., 2020). Methods employed include supervised machine learning, (Bennett et al., 2019, 2020; Bunker & Spencer, 2021; Mosey & Mitchell, 2020), and varied hypothesis testing (Bishop & Barnes, 2013; Bunker & Spencer, 2021; A. Hughes et al., 2017) to analyse the differences in performance indicators between winning and losing team performances.

Key findings in the international men's game include the importance of kicking and lineout success when it comes to quantifying successful match outcomes (A. Hughes et al., 2017). A study by Bunker and Spencer (2021) indicated that ball carry effectiveness and carry and kick metres combined were also identifiers of successful match outcome, whereas Bishop and Barnes (2013) only found kicking and the percentage of penalties conceded between the 50 m and the opposition 22 m lines, as strong indicators of match outcome. These results all relate to team performances isolated from their opposition's performance.

A select number of papers have focused on performance indicators in context of the opposition (Bennett et al., 2019, 2020; Mosey & Mitchell, 2020), in which new PIs are calculated from standard PIs to reflect the differences between two teams within a match. Bennett et al. (2019) identified many relative variables had significant relationships with match outcomes in the English Premiership. This includes relative kicks from hand, clean breaks and average carry distance as well as an additional seven variables (penalties conceded in defence, turnovers conceded, total metres carried, defenders beaten, ratio of tackles missed to tackles made, total missed tackles, and turnovers won). Equally, Bennett et al. (2020) also found these named PIs to be significant drivers of successful match outcomes within international rugby. An additional 10 variables were also found to be significant at the 5% level, including tackle ratio and lineout success (Bennett et al., 2020). Mosey and Mitchell (2020) had similar findings within sub-elite Australian rugby. The following variables were identified to be positively associated with match outcome: kicks in play, metres carried, turnovers conceded and initial clean breaks. In contrast, Bennett et al. (2019) stated that there was a clear improvement in model accuracy, whereas Mosey and Mitchell (2020) identified no clear improvement in model prediction accuracy when using the relative datasets.

However, to date, no key research has investigated the use of variable selection methods to build and validate models, with studies focusing on modelling within a full variable set. In addition, there has also been no evidence of named research within the United Rugby Championship (URC), and limited research in its predecessors the Pro14 and Pro12. Due to this, the first aim addressed in this thesis is to understand the key performance indicators associated with match outcomes in the URC, through the following research questions:

- What key performance indicators are associated with match outcomes in the United Rugby Championship?
- Is there a difference in efficacy of isolated data and data relative to the opposition when predicting match outcome?
- Can models with reduced PIs reproduce similar predictive accuracy?

## 4.3 Methods

### 4.3.1 Data Collation

Data from URC seasons 2017/18, 2018/19, 2019/20, and 2020/21 were downloaded from OPTA in CSV format as described in the general methods. Matches that resulted in draws were excluded from datasets ($n$ = 4,4,1,0 for each season respectively). The remaining dataset included 149 matches from seasons 2017/18 and 2018/19, 103 from 2019/20 and 96 from 2020/21. The datasets were split into winning and losing performances, this created 298 performance data points for 2017/18 and 2018/19, 206 for 2019/20, and 192 for 2020/21.

For evaluation, performance indicators were collected from OPTA for the first ten rounds of the 2021/22 season. This dataset included 53 matches, hence 106 data points in total when split by winning and losing performances.

### 4.3.2 Statistical Methods

#### 4.3.2.1 Hypothesis Testing

The Shapiro Wilk test was utilised to test for normality across both isolated and relative PIs that exist within this dataset. The Kruskal Wallis test was utilised to test for differences in PIs across multiple seasons from 2017-18 to 2019-2020, with Bonferroni used to account for multiple testing. The Dunn test was utilised post hoc to analyse specific differences.

The Mann Whitney U test is a non-parametric hypothesis test useful for data that does not fit the assumption of normality found in other hypothesis testing (Mann & Whitney, 1947). This was used to test for differences between match outcomes and variables in the isolated dataset. Similarly, the Wilcoxon Signed Rank test was utilised to compare differences between match outcomes and variables in the relative dataset, given its contextual relationship between matches. Bonferroni was again utilised to account for multiple testing. Spearman's Correlation Coefficient, r, was used to analyse the correlation between performance indicators in the dataset (Botzoris & Profillidis, 2019).

#### 4.3.2.2 Maximum Relevance Minimum Redundancy

Maximum Relevance and Minimum Redundancy (MRMR) is a feature selection method that allows the selection of predictor variables ensuring the maximisation of the mutual information between predictor and outcome, whilst also minimising the mutual information between other predictors already selected (Sakar et al., 2012). The mutual information value between all variables is calculated as:

$$I(x, y) = \frac{-1}{2} ln(1 - \rho(x, y)^2), \tag{1}$$

where I($x$,$y$) represents the mutual information, and $\rho$ the correlation coefficient of features $x$ and $y$. Pearson has been used as the correlation method between two continuous variables, Cramer's V for two binary variables, and Somers' Dxy was used to compare continuous and binary variables (Jay et al., 2013). MRMR was used to rank performance indicators, this ranking was then used to optimise the number of variables utilised in the final modelling. The r package mRMRe was used to complete this (Jay et al., 2013).

#### 4.3.2.3 Random Forest Modelling

Random forest modelling is a machine learning method that can be used for both classification and regression. The method uses an ensemble of classification or regression trees by drawing a new training set each time, with replacement, from the original sample. Random feature selection is used within each bootstrapped training set, where approximately two-thirds of observations are utilised. Using the out-of-bag (OOB) set, this is the set of values not selected as part of the training set, the tree is tested and the error rate (predictions made incorrectly divided by the total predictions) is noted. This is then averaged for each tree built, to give an OOB error for the random forest model as a whole. Based on the Strong Law of Large Numbers, the modelling process does not tend to suffer from over-fitting (Breiman, 2001).

The Mean Decrease Accuracy (MDA) represents how much the model accuracy will decrease if the variable was removed from the model, high values show that the variable is more important. The prediction error from OOB data is recorded after permuting through each predictor variable. The difference between the model with and without the variable is calculated and averaged over all trees and normalised. MDA was used as the main measure of importance within analysis (Breiman et al., 2022), where the $z$-scores were measured to interpret the significance of importance. The mean minimal depth was also analysed, which is the mean value of where a variable sits on the $y$-axis of a tree, hence lower values suggest a variable tends to sit closer to the root of the tree than higher values.

Random forest modelling was initially completed on the full dataset for both isolated and relative data. The model used all 27 performance indicators in order to classify matches as either wins or losses.

Given the exploratory analysis previously completed, it was clear that many of the performance indicators are highly correlated. Whilst random forest is designed to be robust to high dimensional data and relationships between variables, it has been previously shown that correlated variables can impact a model's ability to identify strong predictors (Gregorutti et al., 2016). This suggested that there was a requirement to manage the number of variables used within modelling to not only improve the identification of strong predictors - the goal of this modelling - but also to simplify the process to improve user interpretation.

Given this, MRMR was used to simplify the dataset. This means the variables were selected in order of maximising the mutual information they have with match outcome, whilst minimising the mutual information shared with the variables that have already been selected. An optimisation loop was created to maximise the models' accuracy in predicting matches, whilst minimising the variables used in modelling. Variables were ordered by their MRMR score, and this was used as a selection order, with the lowest value dropped in each iteration. The dataset was split into five equal groups and random forest models were made for each group based on the number of variables in any given iteration of the loop. Each model's OOB accuracy was measured and a mean across the five models was recorded. The initial models were built with 27 variables, then this was decreased by one every iteration to a final value of two variables in the final iteration. The mean OOB accuracy for each iteration was plotted and the maximum accuracy value was identified. Models within 1% of the maximum accuracy were highlighted, and then the model with the lowest number of variables was selected as the optimal model. A summary of the steps taken can be viewed in Figure 4.1.

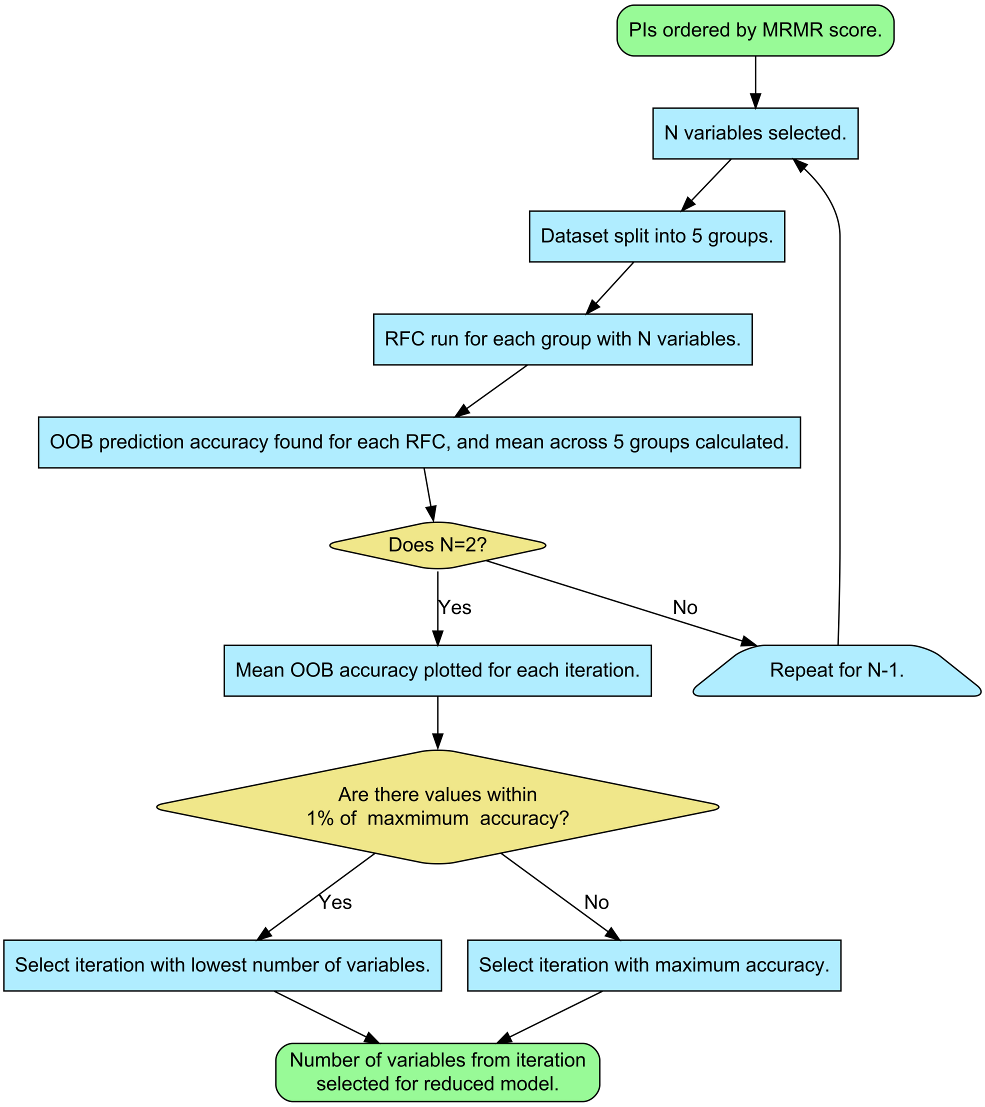



**Figure 4.1**
Flow diagram explaining steps taken within optimisation loop to maximise model OOB accuracy within random forest modelling, whilst minimising the number of variables used in models. Green stages represent the start and end points of the optimisation loop, blue represents the stages throughout and yellow stages indicate decision-making stages.

Once a unique set of variables was chosen for modelling both the isolated and relative datasets, the model parameters were then optimised. A similar loop was used for this. With the data split into five random samples, five models were created and the values for mean OOB accuracy across models were recorded. The variables selected in the previous step were kept the same throughout, but the number of variables considered at each split was changed each iteration instead. Values from one to the maximum number of variables in the model were chosen and tested at one-step intervals. The same metric was used to choose a value for variables considered at each split as before, where the maximum accuracy is identified, and then the lowest number of variables at each split within 1% of this accuracy was selected for further modelling.

Similar optimisation was utilised for the number of trees used within the model, with the number of variables and the variables considered at each split kept the same as before and solely the number of trees changed in each iteration. Tree values between 50 and 2500 were tested at 50 tree intervals. However, the optimised number of trees was maintained the same in both models to allow comparison when the model was permuted, this is due to differences in trees changing permuted accuracy values.

Once modelled, the value for accuracy was calculated for both the isolated and relative model and McNemar's test was used to compare the accuracy of both models. The importance metrics of the variables were also calculated and plotted. Finally, partial dependence plots were used to display how the variables were related to match outcomes across their full range. After a final model was established for both datasets, the model was applied in prediction on the selected rounds of the 2021/22 season.

Random forest modelling was completed using the following packages in r: randomForest, rfUtlities, rfPermute and randomForestExplainer.

## 4.4 Results

### 4.4.1 Exploratory Analysis

Preliminary exploratory analysis was completed on both isolated and relative datasets. Prior to in-depth analysis, multiple seasons were compared using hypothesis testing to decide which dataset to use within further exploratory analysis. After this illustrated key differences in multiple PIs between seasons, particularly in seasons that were distant in time from each other, it was decided that solely the 2020/21 dataset would be utilised further within this research. Within the 2020/21 season, correlation matrix plots were created and hypothesis testing was carried out between winning and losing match outcomes.

#### 4.4.1.1 Normality Testing

Within the isolated sets, based on the Shapiro Wilk test at the 5% significance level, there was no evidence of any variables having a normal distribution for seasons 2017/18, 2018/19 and 2019/20. In 2020/21 there were four variables that accepted the null hypothesis and hence were considered normally distributed. These variables were Carries$_I$ ($p$ = .082), Passes$_I$ ( $p$= .070), Turnovers Conceded$_I$ ($p$ = .052) and Kicks from Hand$_I$ ($p$ = .160).

Within the relative data, more variables were deemed to have normal distributions based on hypothesis testing. These variables varied by season and a full list of all that featured can be found in Table 4.1. Throughout every season, there was a select group that was consistently normally distributed. This group included Carries$_R$, Passes$_R$, Tackle$_R$, Turnovers Conceded$_R$ and Rucks Won$_R$.

**Table 4.1**
Relative variables with normal distributions for each season, based on Shapiro Wilk's test on relative data.

| Season | Variables with Normal Distribution |
|---|---|
| 2017/18 | Carries$_R$, Metres Made$_R$, Offloads$_R$, Passes$_R$, Tackles$_R$, Turnovers Conceded$_R$, Clean Breaks$_R$,<br>Turnovers Won$_R$, Rucks Won$_R$ and Penalties$_R$. |
| 2018/19 | Carries$_R$, Metres Made$_R$, Defenders Beaten$_R$, Passes$_R$, Tackles$_R$, Missed Tackles$_R$,<br>Turnovers Conceded$_R$, Kicks from Hand$_R$, Lineouts Won$_R$, Rucks Won$_R$<br>and Penalties Conceded$_R$. |
| 2019/20 | Carries$_R$, Defenders Beaten$_R$, Passes$_R$, Tackles$_R$, Missed Tackles$_R$, Turnovers Conceded$_R$,<br>Turnovers Won$_R$, Kicks from Hand$_R$, Lineouts Won$_R$, Rucks Won$_R$ and Penalties Conceded$_R$. |
| 2020/21 | Carries$_R$, Metres Made$_R$, Defenders Beaten$_R$, Passes$_R$, Tackles$_R$, Missed Tackles$_R$,<br>Turnovers Conceded$_R$, Kicks from Hand$_R$ and Rucks Won$_R$. |

However, since the majority of variables within the dataset appear to show non-normality, it was decided that non-parametric hypothesis testing methods will be used across the full dataset. This allows consistency throughout datasets and allows comparisons between seasons.

A full breakdown of the Shapiro test for each variable in every season, for both the isolated and relative datasets, can be found in Appendix A.3.

#### 4.4.1.2 Hypothesis Testing - Season Differences

The Kruskal Wallis test was completed for each of the numerical variables in the isolated dataset, to show whether there were statistically significant differences in means across the four seasons. Fourteen variables differed between seasons: Metres Made$_I$, Defenders Beaten$_I$, Offloads$_I$, Passes$_I$, Tackles$_I$, Turnovers Conceded$_I$, Kicks from Hand$_I$, Clean Breaks$_I$, Turnovers Won$_I$, Lineouts Los$_I$t, Free Kicks$_I$, General Play Penalties$_I$, Control Penalties$_I$ and Red Cards$_I$ (Appendix A.4).

The number of variables that differ between seasons has been summarised in Table 4.2. The table indicates a higher number of variables different between 2020/21 and the two earliest seasons, 2017/18 and 2018/19. There were also many variables different between 2019/20 and the two earlier seasons, and the pairs 2017/18 and 2018/19, and 2019/20 and 2020/21 had the least differences.

**Table 4.2**
Number of numerical variables different in each season pair as calculated from the Dunn post hoc test for the isolated data.

| | 2017/18 | 2018/19 | 2019/20 | 2020/21 |
|---|---|---|---|---|
| 2017/18 | - | 4 | 9 | 11 |
| 2018/19 | 4 | - | 10 | 13 |
| 2019/20 | 9 | 10 | - | 7 |
| 2020/21 | 11 | 13 | 7 | - |

A full breakdown of the Kruskal Wallis and Dunn testing for each isolated variable and each season comparison can be found in Appendix A.4. Given that season differences were highlighted for the isolated group, it was decided that a single season would be utilised in modelling for both isolated and relative models to ensure consistency between modelling techniques.

#### 4.4.1.3 Correlation Between Variables

In this analysis, correlation values over a magnitude of 0.5 were considered to focus on high-end moderate and strong relationships (Botzoris & Profillidis, 2019).

Within the 2020/21 season, there were significant relationships between many variables. The main area of high correlation was within attacking metrics. For example, Metres Made$_I$ and Defenders Beaten$_I$ were both positively correlated to Clean Breaks$_I$, with values of 0.67 and 0.55. Carries$_I$ were highly correlated with Passes$_I$ (0.84), Defenders Beaten$_I$ (0.57) and Metres Made$_I$ (0.64). Passes$_I$ were also moderately correlated with many variables including, Metres Made$_I$ (0.59) and Defenders Beaten$_I$ (0.56).

Rucks Won$_I$ was also significantly correlated with many variables, such as Carries$_I$ (0.93) and Passes$_I$ (0.76). Penalties Conceded$_I$ were positively correlated with Tackle/Ruck/Maul Penalties$_I$ with correlation values of 0.59, indicating that it is likely that penalties in these areas were a large percentage of the total conceded overall.

In the relative set, there was also a significant correlation between several of the variables. For example, the correlation between Rucks Won$_R$ and Carries$_R$ and Passes$_R$ were 0.96 and 0.76 respectively, compared to 0.93 and 0.76 in the isolated values. Rucks Won$_R$ was also highly correlated with Metres Made$_R$ (0.6), Passes$_R$ (0.76) and negatively correlated with Tackles$_R$ (-0.98). Rucks Lost$_R$ were also negatively correlated to Turnovers Won$_R$ in the relative data, with a value of -0.56.

The correlation between Penalties Conceded$_R$ and Tackle/Ruck/Maul Penalties$_R$ was 0.67 compared to 0.59 in the isolated values. Penalties Conceded$_R$ were also correlated with Scrum Penalties$_R$ (0.59), meanwhile Tackle/Ruck/Maul Penalties$_R$ were correlated with Ruck Lost$_R$ (0.50).

A key correlation in this dataset that was not observed in the isolated set was between Kicks from Hand$_R$ and Turnovers Conceded$_R$ (-0.55). Equally, Kicks from Hand$_R$ were positively correlated with Turnovers Won$_R$ (0.57). Tackles$_R$ and Missed Tackles$_R$ were negatively correlated with Carries$_R$ (-0.95 and -0.58 respectively) and with Metres Made$_R$ (-0.59, -0.67) and Passes$_R$ (-0.73, -0.55).

Is it important to note that Missed Tackles$_R$ and Defenders Beaten$_R$ have a correlation value of -1, this is because when a tackle is missed, it is considered a defender beaten for the opposition. This means when the data is made relative to the opposition, this variable is the same value, however, negative for one team and positive for the other.

In conclusion, it is clear that there is significant collinearity throughout this dataset. This does not necessarily indicate causality but could have an impact on modelling. A full breakdown of both correlation matrices is illustrated in Appendix A.7.

#### 4.4.1.4 Hypothesis Testing - Win and Losses Differences

The Mann Whitney U test was then applied to the isolated data by wins and losses for the 2020/21 season. Metres Made$_I$ ($p_{adj}$ = .005) and Kicks from Hand$_I$ ($p_{adj}$ = .021) reject the null hypothesis, demonstrating a difference in the winning and losing group at the 5% significance level.

Given the symmetric nature of the relative data, Wilcoxon Signed Rank test was utilised in place of Mann Whitney U test. For the season 2020/21 this gave statistically significant differences in medians between wins and losses for the variables Metres Made$_R$ ($p_{adj}$ = .022), Turnovers Conceded$_R$ ($p_{adj}$ = .032) and Kicks from Hand$_R$ ($p_{adj}$ < .001).

Both the Mann Whitney test statistics and $p_{adj}$ values for all isolated variables in season 2020/21 and the Wilcoxon Signed Rank test statistics and $p_{adj}$ values for all relative variables in season 2020/21 can be found in Appendix A.5. Equally, box plots were created to visualise differences between wins and losses, and a full breakdown of these plots can be found in Appendix A.9.

### 4.4.2 Random Forest Modelling

The initial random forest modelling for season 2020/21 was completed on both datasets. The full model for the isolated data correctly classified 122 match performances out of 192, giving an accuracy rate of 64% with a confidence interval (CI) of (56%, 70%) at the 5% significance level ($\alpha$). Within this, 63 of out 96 wins (66%, CI (55%, 75%), $\alpha$=0.05) were correctly classified and 59 out of 96 losses (61%, CI (51%, 71%), $\alpha$=0.05).

The full model for the relative data correctly classified 159 out of 192 match performances (83%, CI (77%, 88%), $\alpha$=0.05), with 79 out of 96 wins correctly classified (82%, CI (73%, 89%), $\alpha$=0.05), and 80 out 96 losses (83%, CI (74%, 90%), $\alpha$=0.05). McNemar's test was completed to compare the model accuracy and confirmed that the relative model outperformed the isolated model ($\chi^2(1, 192) = 16.00$, $p < 0.001$)).

The full models for both the isolated and relative sets were then simplified using MRMR to optimise variables selected from the full dataset. For the isolated data, the optimisation method found six variables to be the optimum number of features. These variables were Metres Made$_I$, Kicks from Hand$_I$, Turnovers Conceded$_I$, Scrum Penalties$_I$, Turnovers Won$_I$, and Lineouts Lost$_I$. Using this reduced variable set, the parameters for modelling were optimised to give 1650 as the optimal number of trees used in modelling from testing between 50-2500 trees in intervals of 50. Variables tested at each split were set at five, after testing from one to six variables at each split as these were the minimum and maximum variables available to test. The finalised model, given the above parameters and variables accurately classified 126 out of 192 match performances (66%, CI (58%, 72%), $\alpha$=0.05), including 66 wins out of 96 (69%, CI (58%, 78%), $\alpha$=0.05) and 60 losses out of 96 (63%, CI (52%, 72%), $\alpha$=0.05).

Within the relative set, optimisation led to the selection of seven variables for the optimal model. In this set, these variables were Kicks from Hand$_R$, Metres Made$_R$, Scrum Penalties$_R$, Scrums Lost$_R$, Control Penalties$_R$, Turnovers Conceded$_R$ and Clean Breaks$_R$. The optimal number of variables tried at each split was found to be one for the relative model, this was tested between one to seven, to reflect the minimum and maximum variables available in the dataset. However, to maintain the ability to compare models, the number of trees was set to 1650 to match the isolated model. The reduced model correctly classified 163 out 192 match performances (85%, CI (79%, 90%), $\alpha$=0.05), of which it correctly identified 81 out of 96 wins (84%, CI (76%, 91%), $\alpha$=0.05) and 82 out of 96 losses (85%, CI (77%, 92%), $\alpha$=0.05). McNemar's test was repeated demonstrating that the relative data outperformed the isolated data ($\chi^2(1, 192) = 16.40$, $p < 0.001$)).

There was no significant difference in reduced model performance for the isolated models' comparison ($\chi^2(1, 106) = 0.25$, $p = .617$) and for the relative models' comparison ($\chi^2(1, 106) = 0.75$, $p = .386$).

Both full models were also used in prediction on the 2020/21 datasets for rounds of the URC that had been completed at the time of analysis (10 rounds). The full isolated model accurately predicted 77 out of 106 match performances (73%, CI (63%, 81%)), including 39 out of 53 wins (74%) and 38 out of 53 losses (72%). With the full relative model, 96 match performances out of 106 were correctly predicted (91%, CI (83%, 95%)), with 48 of 53 performances correctly predicted in both wins and losses (91%). In prediction, the full relative model outperformed the full isolated model based on McNemar's test ($\chi^2(1, 106) = 24.60$, $p < 0.001$).

Both reduced models were then used in prediction on the 2020/21 datasets. In the isolated dataset, the model accurately predicted 76 matches out of 106 match performances (71%, CI(62%, 80%), including 42 of 53 wins (79%) and 34 of 53 losses (69%). When it was run in prediction on the relative dataset, 95 match performances out of 106 were correctly predicted (90%, CI(82%, 95%), 47 of 53 wins and 48 of 53 losses (89% and 91% respectively). McNemar's test supported that, in prediction, the reduced relative model outperformed the reduced isolated model ($\chi^2(1, 106) = 10.62$, $p = 0.001$)). When the full and reduced models were compared in prediction, there was no evidence of significant differences in performance ($\chi^2(1, 106) = 0$, $p = 1.00$).

It is important to note that of the 11 match performances incorrectly predicted by the reduced relative model, nine were performances where a match was won or lost by six points or less. Four performances were won or lost by one point, two were won or lost by two points and one won by four points. A further two matches were won or lost by six points. Within rugby, this would be considered a close match as a bonus point would be awarded to the losing team. The remaining incorrect predictions related to a match with a points difference of 14 points.

The mean decrease accuracy $z$-scores for each variable in the model have been summarised in Table 4.3, along with the corresponding $p$ values and the mean minimal depth values. Within the isolated model, only five variables were significant. These variables were Metres Made$_I$, Turnovers Won$_I$, Kick from Hand$_I$, Scrum Penalties$_I$ and Turnovers Conceded$_I$, with their related MDA $z$-score ranging from 21.7 to 12.5. These $z$-scores are also plotted in Figure 4.2, indicating a clear divide between Lineouts Lost$_I$, a variable that was not statistically significant in this model, and the rest of the variables which were statistically significant. The mean minimal depth values range from 0.83 to 2.98, within this dataset.

**Table 4.3**
The mean decrease accuracy $z$-scores, associated $p$ values and the mean minimal depth distribution for the simplified model, based on the isolated dataset.

| Variable | Mean Decrease Accuracy $z$-Score | $p$ | Mean Minimal Depth |
|---|---|---|---|
| Metres Made$_I$ | 21.67 | .010 | 0.83 |
| Kicks from Hand$_I$ | 18.15 | .010 | 1.34 |
| Turnovers Conceded$_I$ | 17.28 | .019 | 1.63 |
| Turnovers Won$_I$ | 15.92 | .030 | 2.04 |
| Scrum Penalties$_I$ | 12.49 | .040 | 1.95 |
| Lineouts Lost$_I$ | 4.53 | .158 | 2.98 |

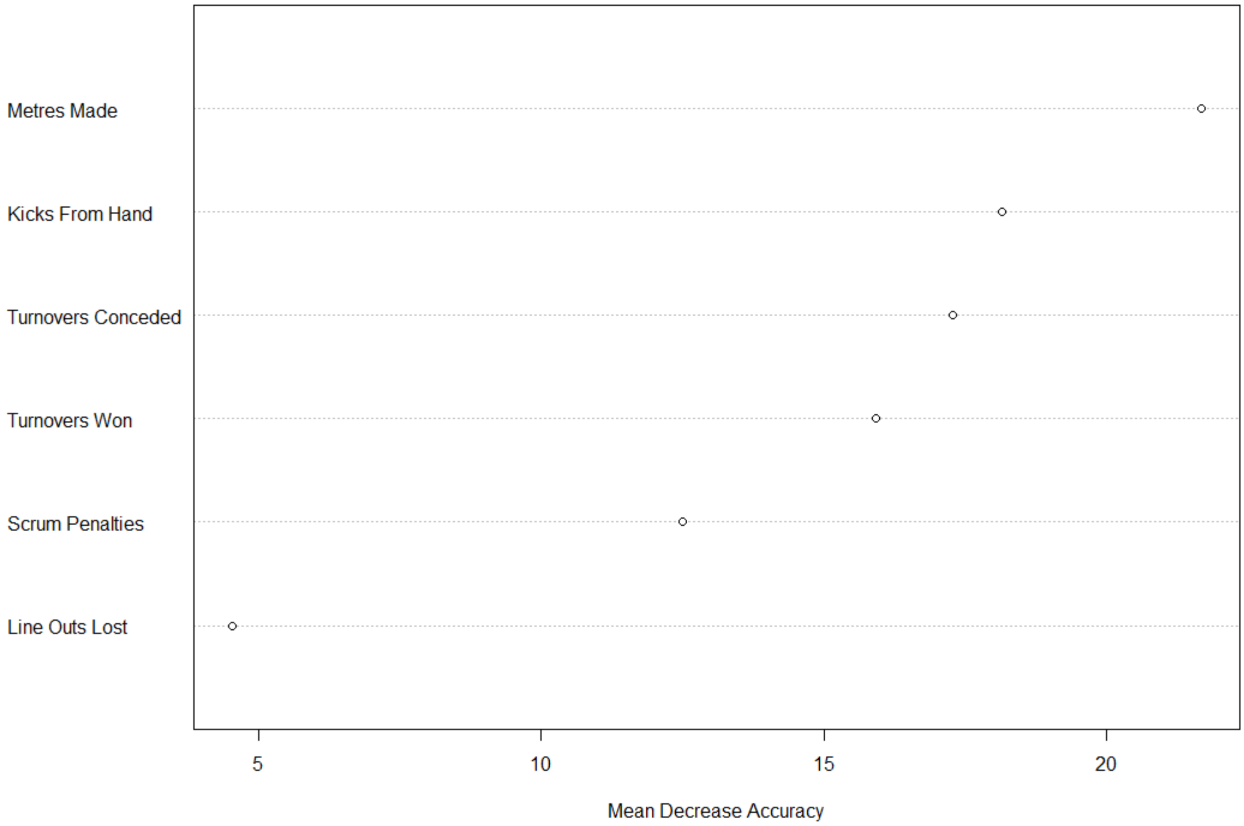



**Figure 4.2**
Mean decrease accuracy $z$-score values by variable in the simplified relative model, this includes Metres Made$_I$, Kicks from Hand$_I$, Turnovers Conceded$_I$, Turnovers Won$_I$, Scrum Penalties$_I$ and Lineouts Lost$_I$.

Within the relative set, only 5 variables were significant, including Kicks from Hand$_R$, Clean Breaks$_R$, Scrum Penalties$_R$, Metres Made$_R$ and Turnovers Conceded$_R$. The range of MDA $z$-scores was much larger for significant variables in the relative set (51.6-17.7), this is due to Kicks from Hand$_R$ having a much higher value of MDA $z$-score than the rest of the group. For this group, a small range of mean minimal depth was observed (2.3-2.5). Figure 4.3 highlights the striking difference in MDA $z$-scores between Kicks from Hand$_R$ and the rest of the variables. A full breakdown of these values can be viewed in Table 4.4.

**Table 4.4**
The mean decrease accuracy $z$-scores, associated $p$ values and the mean minimal depth distribution for the simplified model, based on the relative dataset.

| Variable | Mean Decrease Accuracy $z$-Score | $p$ | Mean Minimal Depth |
|---|---|---|---|
| Kicks from Hand$_R$ | 51.63 | .010 | 2.4 |
| Metres Made$_R$ | 25.25 | .010 | 2.4 |
| Clean Breaks$_R$ | 25.21 | .010 | 2.3 |
| Turnovers Conceded$_R$ | 24.76 | .010 | 2.5 |
| Scrum Penalties$_R$ | 17.66 | .010 | 2.3 |
| Control Penalties$_R$ | 1.89 | .356 | 2.3 |
| Scrums Lost$_R$ | 0.27 | .455 | 2.3 |

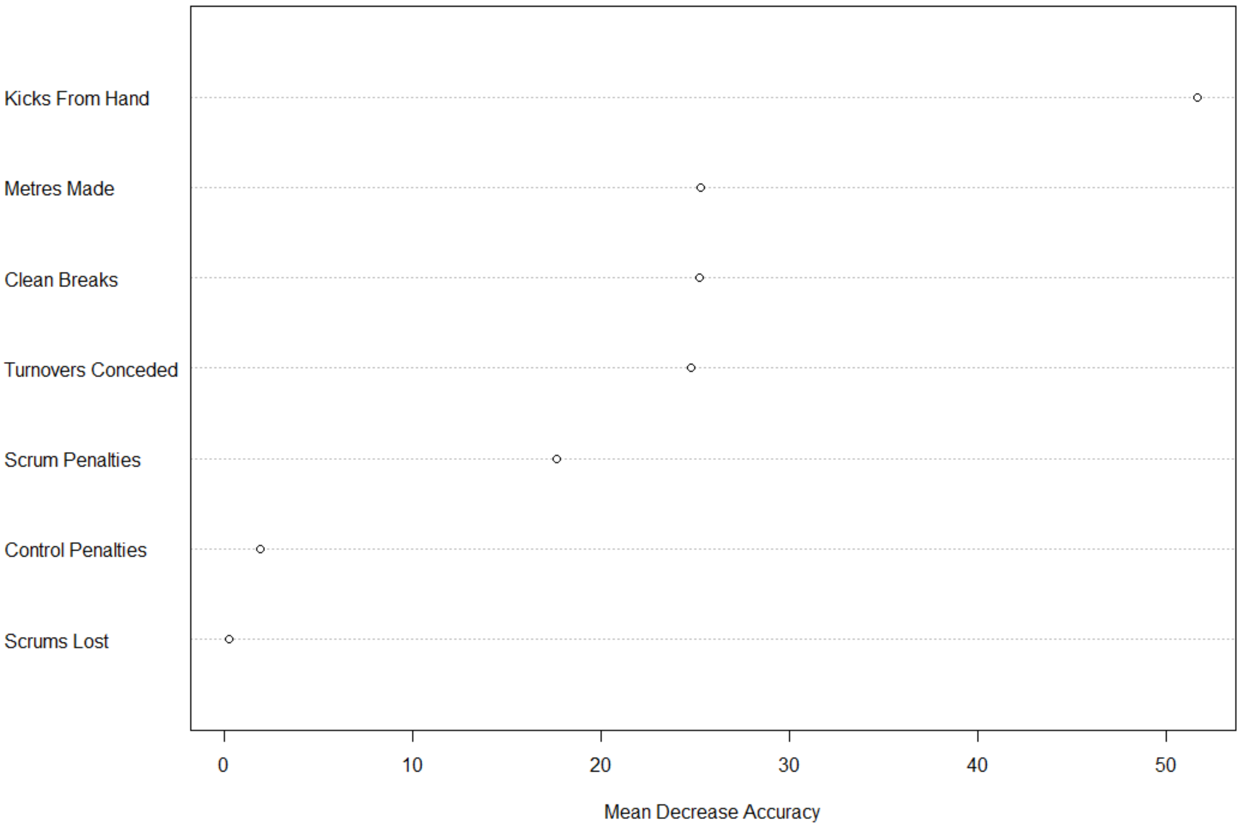



**Figure 4.3**
Mean decrease accuracy $z$-score values by variable in the simplified relative model, this includes Kicks from Hand$_R$, Metres Made$_R$, Clean Breaks$_R$, Turnovers Conceded$_I$, Scrum Penalties$_R$, Control Penalties$_R$ and Scrums Lost$_R$.

Partial dependence plots were created for all statistically significant variables within the models, based on their MDA $z$-score. Within the isolated model, positive associations were observed between wins and Metres Made$_I$, Turnovers Won$_I$ and Kicks from Hand$_I$. Conversely, the negative association between wins and Scrum Penalties$_I$ and Turnovers Conceded$_I$. Many of these relationships tail off, where there is a limit at which increases or decreases in the values of the variable do not contribute any further to the probability of winning. This can be observed for Turnovers Won$_I$, where values above nine turnovers won per game had a negligible impact on the increasing probability of winning. Equally, after six Scrum Penalties$_I$ there was no obvious decrease in the probability of winning.

For the relative set, Kicks from Hand$_R$, Clean Breaks$_R$, and Metres Made$_R$ were all positively associated with winning, whereas Scrum Penalties$_R$ and Turnovers Conceded$_R$ were negatively associated. With Kicks from Hand$_R$, there was no obvious increase in the probability of winning after taking 10 additional kicks than the opposition or decrease after conceding 10 additional kicks. Similarly, within Metres Made$_R$, after approximately 300 or -300 metres made there was no increase or decrease in the probability of winning respectively. Clean Breaks$_R$ had a similar relationship, with no increase in the probability of winning after 10 additional clean breaks, and no decrease after conceding -10 additional clean breaks.

For Turnovers Conceded$_R$, there was no clear limit to the probability of winning. Scrum Penalties$_R$ tended to have a negligible increase in negative impact on probability after five additional penalties, and no clear increase in winning with less than five penalties.

All partial dependence plots can be viewed within Appendix A.10.

## 4.5 Discussion

The primary focus of this chapter was to understand key PIs associated with match outcomes in the URC. The secondary aims were to test the difference between isolated and relative data and to investigate whether the reduced models can be used without degrading model efficacy in prediction. Results have shown in both datasets, that kicks from hand, metres made, clean breaks, turnovers won or conceded, and scrum penalties were key variables in differentiating between successful and unsuccessful performance within URC matches as observed in Table

4.4 and Table 4.3. This chapter corroborated what had previously been recognised within literature (Bennett et al., 2019), that a team's performance data is more efficient at predicting match outcome when it has been put into the context of the opposition's performance. The chapter also demonstrated the predictive capabilities of smaller datasets, illustrating that selecting a much smaller set of variables does not negatively impact a model's effectiveness in this context.

Initial data reduction analysis established that multiple variables were significantly different between seasons, however seasons closer together in time featured less differences. This suggests that staying up to date with the most recent season is important when interpreting what is key to a successful performance. Similarly, after a certain time frame, the previous analysis completed may not be representative of the game at the current time. COVID-19 is another consideration when analysing between seasons, with some studies highlighting the impact of the pandemic on international play. Sedeaud et al. (2021) demonstrated that home advantage was reduced in the 2020/21 seasons of professional rugby in Europe, with away victories increasing when fans were not allowed to attend matches. This suggests that crowds have a big impact on home advantage, and that during the COVID-19 pandemic, this impact may have been minimised by legislation changing fans' ability to attend matches. This may explain the lack of significance in home and away advantage seen within this chapter's results. From another perspective, Costello et al. (2022) described unprecedented changes to squad selection due to the pandemic. In this case, the study documents a professional team's reliance on academy players, who are generally younger and less experienced than senior players, during a pivotal game within the season. This reliance was due to a number of players being unavailable due to either contracting COVID-19 or having to isolate due to being a close contact. This hints towards struggles in performance during this period, related to player availability.

Kicking was significant within both datasets, however, when data was made relative, kicks from hand became more important (related to a 51.6 value in MDA $z$-score compared to 21.7 MDA $z$-score in the isolated model). The importance value demonstrated the loss in accuracy when removed from relative modelling, which illustrates the value this variable has in differentiating between wins and losses. This suggests that teams who kick more than their opposition are more likely to win.

Over time, the nature of kicking has changed within rugby (McCormick, 2019). Kicking can be completed for many reasons such as for territorial or tactical advantage. Kicks can also be made under pressure to either move out of a team's own 22 or to slow down and allow a team to restructure their defence. It is unclear from these results whether these kicks have been intentional tactical plays or under pressure, this is something that could be useful to research further from a practical applications perspective. It may be that promoting tactics that allow a team to ″one up″ their opposition in kicking may be beneficial to success. This may be from using box kicks in a vulnerable position in conjunction with pressure up on the opposition, kicks for touch, kick chase tactics and also ″winning the kicking battles″. The latter refers to periods of play where teams exchange many kicks in a row, this research may suggest that both starting and finishing these battles could be another area that would assist with increasing relative kicks from hand within a match. It is clear that further research is needed to interpret what causes relative kicks to be good indicators of success and whether the above tactics can be observed in winning teams. Understanding kick types, positioning, and outcomes is key to interpreting the benefit of relative kicks in winning teams.

Kicking is likely to become even more important with the introduction of the 50:22 rule, which states that if a team kicks from inside their own 50 m, into touch within the opposition's 22 m they will be awarded the throw-in for the lineout (World-Rugby, 2021). This rewards longer distanced kicks and gives a tactical advantage towards the kicking team, in turn putting the opposition under significant pressure in their own 22 m.

In the literature, kicking is often a strong differentiator between winning and losing outcomes, Bennett et al. (2019) also established that relative kicks from hand were important within the 2015 Men's Rugby World Cup. Within the same competition, A. Hughes et al. (2017) discovered winners kicked more in the opposition 22-50 m compared to losing teams, however, the same results were not observed in the Women's 2014 World Cup. This suggests that results are distinct between genders. Using a different method, Bishop and Barnes (2013) also identified kicks from hand to be significantly different between wins and losses in the

2011 Men's World Cup. Mosey and Mitchell (2020) also found that relative kicks were positively associated with winning performances within the Australian sub-elite rugby. It is clear that in modern Men's rugby, kicking is a key area of interest when it comes to successful performances worldwide. This is a key finding from this chapter, and informs further research scope within this thesis. With the key focus of this chapter being simplification of key PIs, this result allows the evolution of solely kicking performance as the thesis proceeds.

Other attacking metrics, such as metres made and clean breaks, were also ranked highly within the relative model, demonstrating the importance of a strong attack. Making metres may seem an obvious way to promote a more successful performance against the opposition, especially when considered relatively. The more metres made is an indicator of not only possession but success in possession by moving forward with the ball. It is not surprising that this variable is important in both datasets. Clean breaks featured in the relative model only and was the third most important variable based on MDA $z$-score. This suggests that it is not making clean breaks alone that is the key to successful match outcomes, but the ability to make more than the opposition or prevent the opposition from executing successful clean breaks themselves. Previous research has also demonstrated that clean breaks and metres made can both differentiate between winning and losing performances within 2015 World Cup matches (Bennett et al., 2019). Mosey and Mitchell (2020) also reported identical results when considering winning performances in sub-elite Australian rugby.

Another key area of importance from both datasets is the breakdown, with turnovers conceded and won being significant important variables within the isolated model. Is it clear that within the relative model, these variables will be very similar when they are contextualised, so the fact that only one remained after feature selection is not surprising. This suggests that conceding fewer turnovers to the opposition is key to winning matches, or alternatively forcing more turnovers from the opposition. This may assist with the improvement of other metrics mentioned previously, such as metres made, by increasing possession. In Mosey and Mitchell (2020), analysis of PIs also reported identical results with less isolated and relative turnovers both consistent with winning performances.

Discipline, especially around the set piece, is also considered important based on MDA measures displayed in Tables 4.3 and 4.4, namely in the form of scrum penalties. Over time, the nature of the attitude towards scrums has changed, with packs getting heavier (Hill et al., 2018), law changes and the standard tactical substitution that leads to the front row being entirely replaced during a match becoming the norm. The existence of a stolen scrum has become very uncommon within professional rugby with the average in the URC 2020/21 season being 0.47 per match. With that comes a requirement to find another tactic to force a turnover in the scrum and hence scrum penalties become more important to the game. The team's ability to control their own scrum and also put pressure on during an opposition scrum is key to forcing the opposition to concede scrum penalties. Teams can then use awarded penalties to either kick for points or gain a tactical or territorial advantage. Previous research has yet to identify scrum penalties specifically as a key contributor to success, but it has identified penalties conceded as a whole as a key PI (Bennett et al., 2019; Bishop & Barnes, 2013; Vaz et al., 2019).

Whilst random forest modelling is a recognised and popular modelling technique within rugby (Colomer et al., 2020), feature selection has not been used previously within key literature. Bunker and Spencer (2021) discusses machine learning literature and develops its practical application within sports prediction. The method is not dissimilar to methods used in this chapter, with acknowledgement to differences in separate seasons of sports and references to different data feature selection options, although direct methods used were not specifically mentioned. The paper discusses the opportunities of machine learning within this area, but does not apply them to real-life datasets like what has been completed in this thesis. Using a feature selection method has allowed the model to hone in on what key variables are driving successful performance, whilst removing highly correlated variables from within the model. This is useful both in reducing the noise in the modelling, but also within practical applications of this research. Removing variables has simplified the modelling process, and promoted the interpretability of results. Within this analysis, it was confirmed that the optimised and simplified models did not degrade model efficacy compared to the initial full models ($\chi^2(1, 106) = 0$, $p = 1.00$).

The use of the relative model was effective in prediction, with 90% of match performances correctly classified. The fact that the majority of errors (9 out of 11) were from games that had a points difference of 6 points or less, suggests that close matches may be more difficult to predict (Vaz et al., 2011). This is relevant to the laws of the game as in rugby, any team who loses by 7 points or less is awarded a bonus point (United Rugby Championship, 2025).

Within a professional rugby environment, the reduced feature set can be utilised by a practitioner to focus on a manageable set of key parameters that can be improved within strength and conditioning and tactical training. Long term, it has the potential to simplify monitoring practices that may take place to understand the strengths of opposition teams. It also removes the ″repetition″ of important variables, for example, metrics such as defenders beaten and clean breaks, which are highly correlated due to the nature of the relationships within the game itself. These variables are likely to be attached to a single event within the match, hence it may not be beneficial for practitioners to necessarily focus on both, and model simplification helps with this.

In Bunker and Spencer (2021), the study combined both metres made by carries and metres made by kicks together as a variable and identified this contributed towards success in the 2015 Rugby World Cup. Although it is not a direct combination, this is an associated view of two key variables found to be important within this chapter's results. This hints at something greater that is both a strength and limitation of research within this area: the use of multiple sets of PIs. There is generally observed to be a lack of consistency in performance indicators used throughout this area of research (Colomer et al., 2020), this is likely due to different collection methods used within studies. Many studies code and collect their own PIs from video footage using different methods such as in Vaz et al. (2019), whereas others, including the results of this chapter, use data collection services such as OPTA. This means that the performance indicators collected are often different. Furthermore, as many data collection companies collect hundreds of variables in a single game, it would be inconceivable for researchers to use full datasets for analysis. This also creates a divide as to which variables are included, even within data collected from the same source. When comparing studies, while key themes can be brought together, it is difficult to compare in depth the similarities and differences within literature due to this. Furthermore, this is also impacted significantly by the augmentation of datasets with additional calculated PIs. These PIs can be more useful in differentiating between match outcomes as demonstrated in this chapter, however, they can also lead to further variations observed throughout the literature. The key conclusion here is that when comparing to literature it is essential to focus on themes of performance such as carries or kicking metrics, rather than specific PIs.

Future research should include further analysis of the key variables identified above, with further detailed context as to time and field position considered to gauge a better understanding as to why these variables are important when it comes to measuring success. The first pathway is to investigate kicking as, unlike the other four variables, it is not an obvious driver of success observed from a professional coaching and analysis perspective. The fact that it is observed as the most important within modelling is striking and requires more in-depth research into why it is such a strong indicator of success. It is essential to interpret relative kicks at a sequence level to understand how the small outcomes may add up to a match-winning performance. Kick types, distances and outcomes may all also give further understanding of kicking's importance within rugby. Hence, the next chapter will aim to investigate kicking at the sequence level, hoping to uncover what is driving successful performances.

## 4.6 Practical Applications

Practical applications of this research include the use of relative in place of isolated statistics, meaning teams should take into consideration opposition when optimising tactics within competitions. This research also suggests that maximising kicks from hand in-game is fundamental to match-day success, therefore teams can use this within their tactics to improve performance. Carrying PIs such as metres made and clean breaks are also vital, and understanding how these metres are made and by who, as well as how clean breaks occur, are both key to successful performances. Furthermore, focusing on maintaining possession as well as aiming to turn over the opposition ball is another key place where teams can benefit. Finally, the inclusion of scrum penalties suggests that focus on discipline and structure within set-piece play is another area that should be managed within tactical training. Strength and conditioning could also be tailored for relevant players to assist with scrum strength and stability.

## 4.7 Limitations

For variables within the dataset, the specifics as to the field position and time are not given, which is a key limitation. Certain variables that have been considered, specifically kick from hand and scrum penalties, may have different impacts on match success both in different areas of the field and at different times during a match. For example, penalties within a kickable distance of the posts may be more related to successful outcomes, as well as penalties nearer the end of a match may also lead to changes in match outcome. Understanding the time and field context of these variables could impact the relationships between wins and losses, and the inclusion of further in-depth PIs may assist in further analysis.

In addition to this, research has taken place within professional football that indicated that normalising PI's with context of possession led to higher information gain, improved model performance and increased interpretability of modelling (Phatak et al., 2022). This transformation could be considered as an equivalent measure to give more context to data, such as the relative transformation done in this chapter and previous research (Bennett et al., 2019, 2020), however, it could also be considered as an additional measure. Using both a relative measure, and giving context to possession may improve machine learning modelling performance and interpretation in any future research within this area.

This research is also limited to team statistics, whereas it may be more helpful from an application perspective to understand how individuals in different playing positions contribute to each variable. Aggregating performance indicators in this way may lead to a further understanding of what drives success and how to implement this in a professional rugby environment.

Furthermore, this research has been limited to within the URC and the competition's predecessors. Its application to other rugby competitions or international level competitions is unknown.

## 4.8 Conclusions

The primary aim of this analysis was to define what success means within the United Rugby Championship, more specifically, what performance indicators are important predictors of wins or losses within the competition. Secondary aims here include investigating whether isolated and relative data perform better and if modelling datasets could be simplified without sacrificing effectiveness in prediction.

It is clear that kicks from hand, metres made, clean breaks, scrum penalties and turnovers won and conceded are key to predicting match outcome. Furthermore, data that is relative to a team's opposition is more effective at differentiating and predicting between wins and losses. The importance of feature selection was highlighted as well as the fact that model effectiveness does not necessarily suffer when smaller sets of variables are used.

It was also established that PIs tend to change from season to season and that contiguous seasons tend to be more similar. Further research in this scope is required to understand whether this is impacted by changes in league structure, coaching changes and COVID-19 issues.

# 5 How does relative kicking influence success at the sequence level?

## 5.1 Abstract

**Background** Relative statistics have been recently introduced to performance analysis within rugby, where their use has improved model efficacy in the professional men's game. Analysis has focused on the use of these statistics at the match level, however, there is yet to be any investigation on their implication at the sequence level – where players may have more control over direct actions.

**Aims** The aim of this chapter is to interpret how relative kicking influences matches at the sequence level.

**Methods** Coded video analysis files were downloaded from 144 matches within the 2021/22 season of the United Rugby Championship. Sequences containing kicks were isolated and the kicks in each sequence were collected ($n$ = 6587). For each sequence, the number of kicks for each team was totalled and the relative kicks were calculated from the perspective of a reference team. The outcome of each sequence was obtained and defined as a positive, negative, or neutral outcome. The proportion of each sequence outcome was plotted across the different values of total and relative kicks, and this process was repeated for different kick types. Kruskal Wallis testing was utilised to compare relative kick values between outcomes.

**Results** The most common value of relative kicks in a sequence was +1 kicks, with significant differences between kick outcome and the relative kicks per sequence (H(2, 3759) = 389.2, p < .001). Increased relative kicking was associated with a decrease in negative outcomes and increases in neutral outcomes. Increased relative box kicks were linked to neutral outcomes whereas territorial and low kicks were associated with positive outcomes. The majority of tries scored in kicking sequences were scored when the reference team made one additional kick than their opposition (51%).

**Conclusion** These results indicate that relative kicks are built across many sequences within

a match, and through different kick types. The increase in neutral outcomes but also try scoring outcomes when relative kicks increase suggests that a combination of territorial and possession-based kicking tactics are required to create a successful kicking strategy.

## 5.2 Introduction

In Chapter 4, five key variables were highlighted as significantly associated with winning match outcomes in rugby. These were relative measures of kicks from hand, metres made, clean breaks, turnovers conceded and scrum penalties. Metres made and clean breaks are both clear attacking measures, and hence it is intuitive that winning teams would perform these more than their opposition. Equally, turnovers conceded and scrum penalties both lead to conceding possession to the opposition and the latter can also lead to conceding points via penalty kick. These four PIs have a clear interpretation within the game so it is easy to understand, from a practical perspective, why they are good differentiators of winning and losing. However, when kicks from hand are examined, their strength as an indicator of success is less intuitive, with the influence of this action more complex in matches. When the ball is kicked, despite the possible gain in territory, the risk of losing possession is high. Unlike the previous metrics, which all relate to either recovering possession or capitalising when in possession, kicks from hand may have different anticipated outcomes, depending on several factors. Previous research is yet to give any further conclusions other than to increase kicking and kick more than the opposition (Bennett et al., 2019, 2020; Mosey & Mitchell, 2020). This leads to the question, how do you utilise kicking to promote success and what are the contextual factors that are associated with this success?

Chapter 4 focussed on team data that was aggregated over a full 80-minute match, but this does not provide insight into what is happening play-by-play to lead to a team's success. Greater context is required to understand why kicking leads to match success and what teams, and individuals, do at the play-by-play level to build up to a successful match overall.

There has been limited research into kicks from hand within rugby, with the majority of kicking research limited to place kicking (Bezodis et al., 2017; Pocock et al., 2018; Quarrie & Hopkins, 2015). This is a different concept to kicking in game, as it is not during active team play and is completed by an individual whilst other team players stand aside rather than in conjunction with active players moving on the field. Many studies have analysed the biomechanical requirements of kicks, the likelihood of success given kick placement or attempts to understand the different contextual factors and their implications on goal kicking success (Pocock et al., 2018; Quarrie & Hopkins, 2015). Some of these factors, such as pitch location, may still have an impact on kicks in play.

Research into sequence outcomes is extremely limited within rugby. Two studies have investigated what ″positive″ and ″negative″ outcomes are within rugby sequences. The first of these studies investigated outcomes based on whether territory was gained or lost, possession was gained or lost, a try was scored or whether a penalty was won or conceded in possession. Watson et al. (2020) focussed on these outcomes for both phases and possessions, leading to ten possible outcomes at each level. This method does not consider the possibility of neutral outcomes, and with ten outcomes available, this method may complicate messaging. For example, there may be overlaps in what leads to positive outcomes in each circumstance. A second research group avoided the use of positive and negative markers by using a methodology that categorised sequences as scoring and non-scoring outcomes (Bunker et al., 2021). However, while the previous chapter has proved kicks from hand are associated with winning matches, it has not identified whether this is from direct points-scoring opportunities or whether kicks are used both defensively or in conjunction with non-kicking sequences to lead to scoring. Therefore, comparing scoring and non-scoring outcomes may not hold the definitive answer to why kicking is successful.

More research is required to understand the implication of kicking at the sequence level and its consequent link to success within professional rugby, in particular the URC. This chapter therefore aimed to interpret how relative kicking influences matches at the sequence level by answering the following research questions:

- What is the frequency of relative kicks across sequences?
- Is there an association between relative kicks and sequence outcome?
- Are there differences in relative kicks by kick type?

## 5.3 Methods

### 5.3.1 Data Selection

Given the high predictive accuracy within the previous chapter, the 2021/22 season data was used within this current chapter to analyse kicking. This dataset was extended to include all 144 matches across the full season, excluding knockout and final matches. This section focussed on kicking sequences only, with 3759 sequences, containing a total of 6587 kicks. The nomenclature of +1 and -1 kick was used throughout this chapter to denote one additional kick or one less kick than the opposition respectively.

### 5.3.2 Statistical Methods

#### 5.3.2.1 Visualisation

Probability density histogram plots are a variation of a histogram plot. While histograms demonstrate the frequency of values of a dataset across its range, density histogram plots illustrate an estimate of the probability density value across the range. This allows comparison between datasets with different ranges. Probability density plots were used to analyse the transformation from isolated to relative kicks per sequence.

Stacked proportion plots are a variation on a column chart, where instead of presenting the data side by side, the different bars are ″stacked″ on top of each other. When this is completed for proportion, the entire ″stack″ indicates 100% of the data and is separated into multiple stacks, usually coloured differently. This method of plotting allows the comparison of the proportion of variables across different groups easily. Proportion plots were used to visualise positive, neutral and negative sequence outcomes across different groups. This was used to analyse relative kicks overall and by kick type.

#### 5.3.2.2 Hypothesis Testing

The Kruskal Wallis test with Bonferroni correction was used to compare relative kicks between positive, neutral and negative outcomes, with the Dunn test utilised as a post hoc test. This process was repeated for relative kick values between kick types and detailed outcomes.

## 5.4 Results

Density histograms of kicks per sequence for the 2021/22 season data are illustrated in Figure 5.1. A density histogram of the total kicks made within each sequence from both teams can be observed in Figure 5.1A, where the histogram covered a range of kicks from a minimum of one kick per sequence to a maximum of ten kicks per sequence. This distribution had a positive skew of 2.4, indicating that it is highly skewed to the right, with the majority of kicking sequences only featuring one kick.

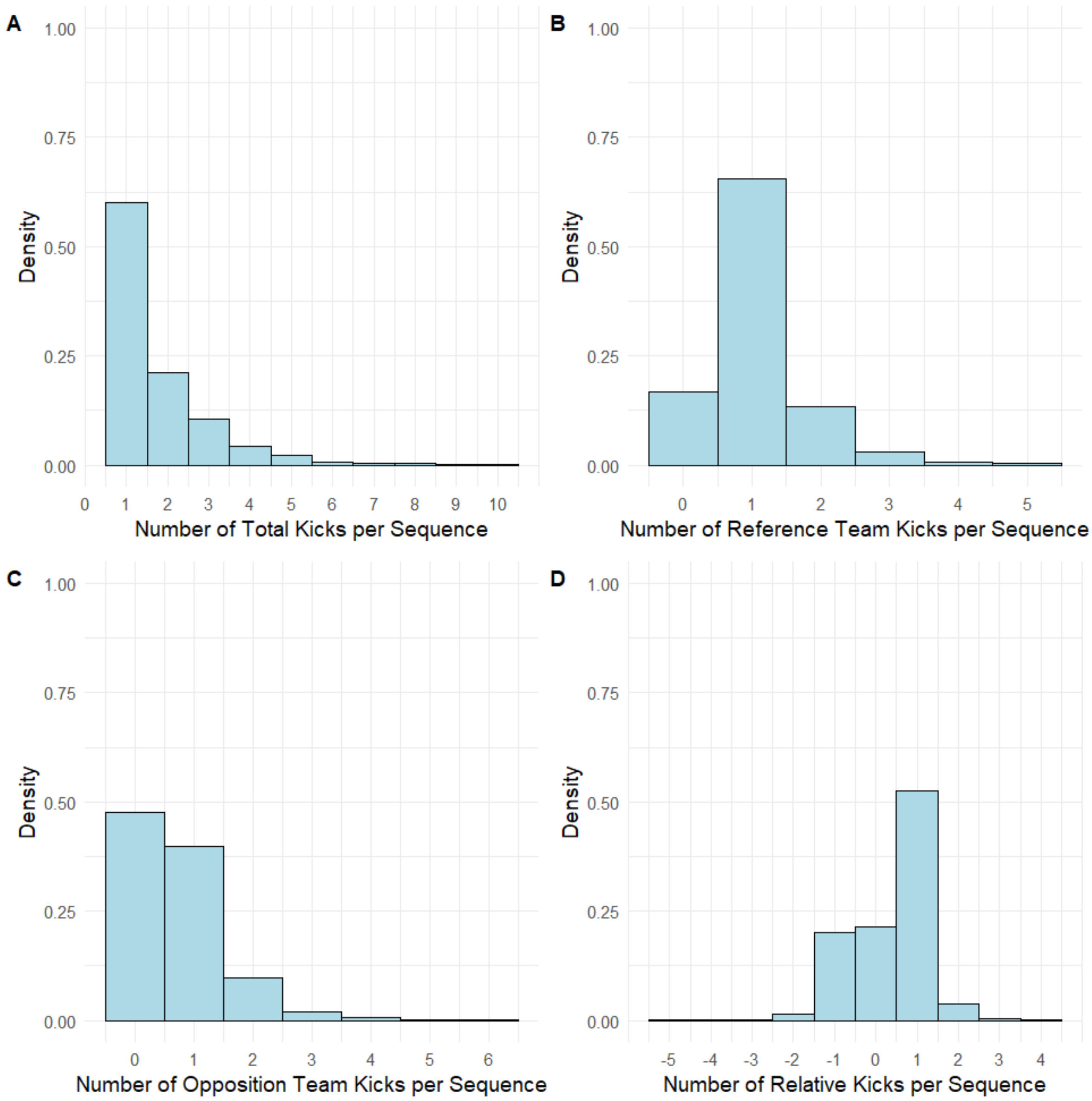



**Figure 5.1**
Plot A displays the density histogram of total kicks per sequence and plot B displays the density histogram of the reference teams' kicks per sequence with the team in possession at the end of the sequence as the reference team. Plot C displays the density histogram of opposition team kicks per sequence, and plot D displays the density histogram of relative kicks per sequence of the reference team.

The reference team (the team in possession at the end of the sequence) kicks ranged from zero to five kicks per sequence. The most common number of kicks for the reference team was one (66%), followed by zero (17%) and then the frequency density tails off as the number of kicks per sequence increases (Figure 5.1B). This distribution had a skewness of 1.3, demonstrating a positive skew but lower skewness than the total kicks. Conversely, for the opposition team (Figure 5.1C), the kicks ranged from zero to six and the most common number of kicks was zero (48%), closely followed by one kick per sequence (40%). The frequency density values for two kicks or more rapidly decreased across the range. The skewness for this distribution was similar with a positive skew of 1.5.

The majority of sequences ended with the reference team making +1 kicks than their opposition. Within the distribution of relative kicks, the minimum value was -5 (<0.05%), indicating that the team in possession at the end of the sequence conceded five more kicks than they made. The maximum value for relative kicks was +4, indicating that the reference team made four more kicks than their opposition. The skewness for this distribution was lower in magnitude and negatively skewed (-0.6). The majority of kick sequences contained either -1, 0 or +1 kicks, with the relative proportion being 20%, 21% and 53% respectively.

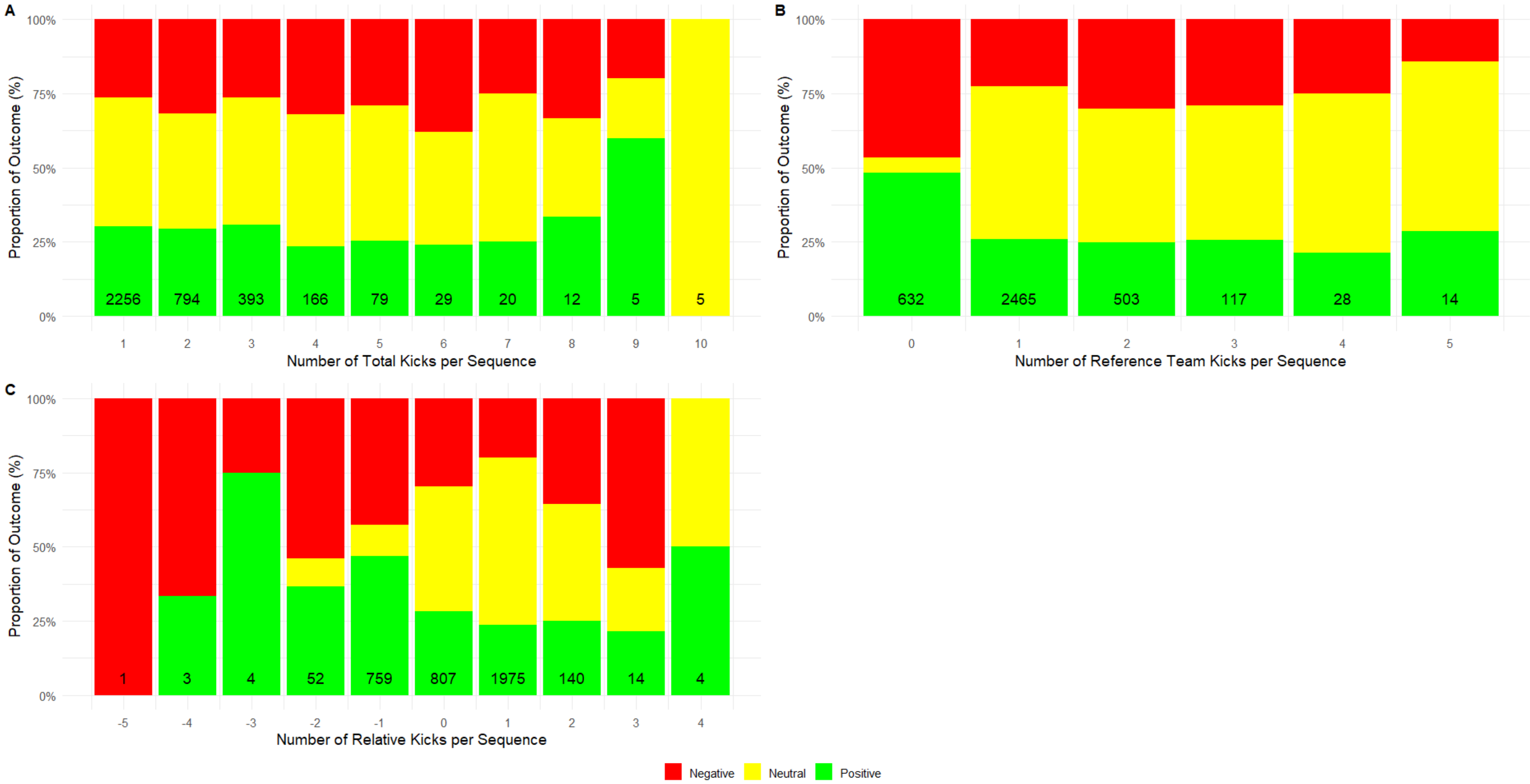



**Figure 5.2**
Plot A illustrates the outcome proportion plot of total kicks per sequence whereas plot B illustrates the outcome proportion plot of reference team kicks per sequence, with the team in possession at the end of the sequence as the reference team. Plot C illustrates the outcome proportion plot of relative kicks per sequence for the reference team. The count of sequences with each kick or relative kick value is displayed at the bottom of the column. Red indicates negative outcomes, yellow displays neutral outcomes and green represents positive outcomes.

In Figure 5.2A, there was no obvious change in outcomes across the different numbers of total kicks. There were fluctuations across the positive, neutral and negative outcomes but no clear relationship across the range of the data. This was confirmed by Kruskal Wallis test, identifying no significant difference in median total kicks values between outcomes (H(2, 3759) = 2.77, $p$ = .250).

Figure 5.2B indicates that sequences containing one kick or more than the reference team tended to have a large proportion of neutral outcomes when compared to when zero kicks are completed by the reference team. Figure 5.2B also suggests a small increase in neutral outcomes and a decrease in negative outcomes after two total kicks. There is a slight decrease in negative outcomes from two kicks to five kicks, but no clear increase or decrease in positive outcomes in this range (Figure 5.2B). The Kruskal Wallis test confirmed differences in the median of reference team kicks between outcomes, (H(2, 3759) = 215.81, p < .001). The Dunn test found significant differences between neutral outcomes compared to both positive and negative outcomes (Appendix B.2).

In contrast to Figure 5.2, Figure 5.2C indicates a noticeable relationship between outcome and the number of relative kicks per sequence. Specifically, the negative sequence outcomes decrease as the number of relative kicks increases between -2 and +1 relative kicks. After zero, there was a sharp increase in neutral outcomes. The positive outcomes do not have a clear relationship, they tended to fluctuate and then decrease between -1 and +3 before increasing at +4 kicks. Kruskal Wallis test confirmed differences between median relative kick values between outcomes (H(2, 3759) = 389.2, p < .001). Dunn testing demonstrated significant differences between all three outcomes (Appendix B.2).

This data were split by kick type, and the outcome analysis was repeated. For example, +1 box kicks would mean a team has completed one additional box kick than their opposition regardless of any other kick types made in the sequence. If no kicks of the type were made, the sequence was removed from visualisation and hypothesis testing.

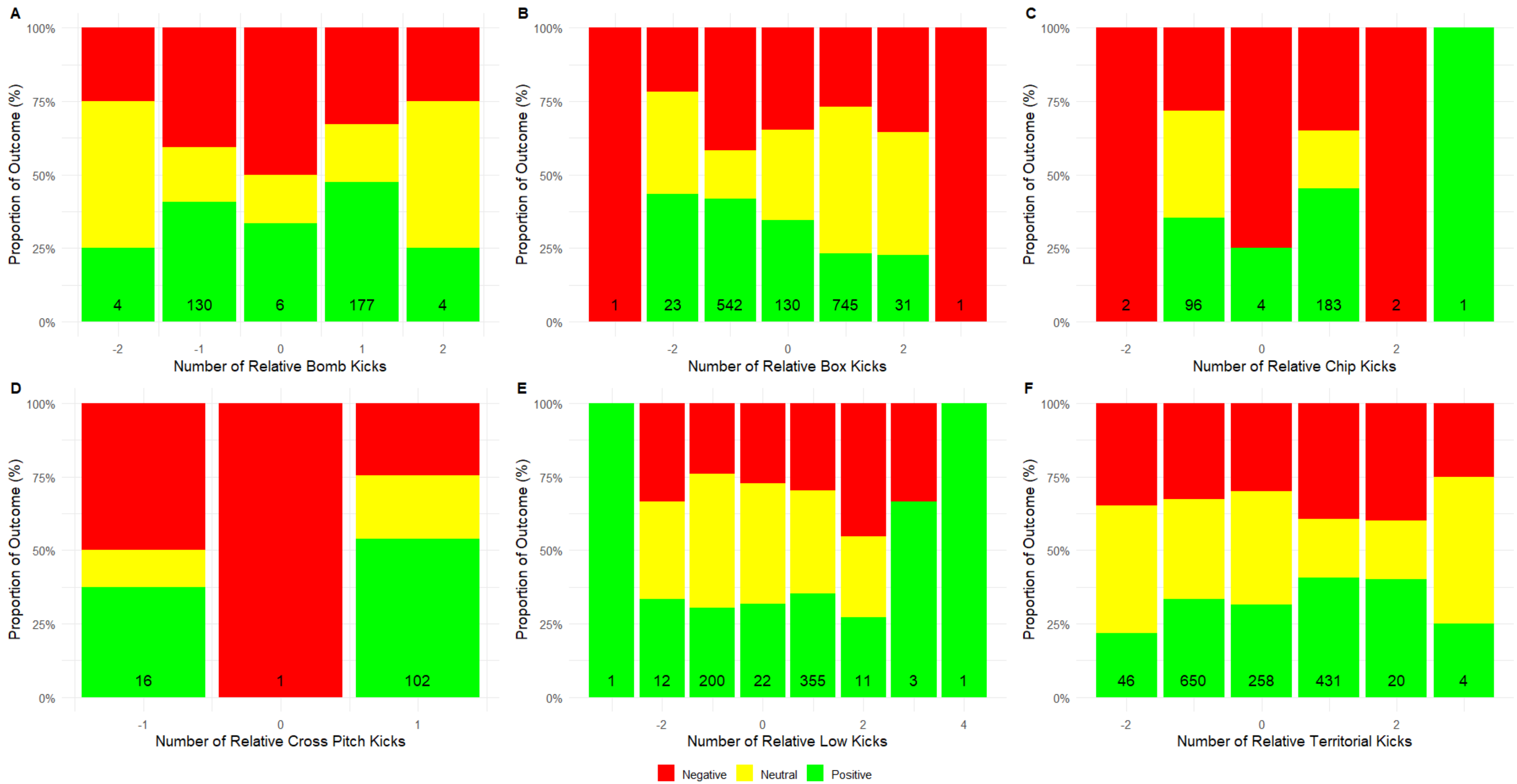



**Figure 5.3**

Figure A-F illustrates the outcome proportion plot of relative kick types per sequence with reference to the team in possession at the end of the sequence. Plots A, B, and C represent bomb, box and chip respectively, whereas D, E and F illustrate cross pitch, low and territorial. The counts of sequences featuring relative kick counts for each type is displayed at the bottom of each column. Red indicates negative outcomes, yellow displays neutral outcomes and green represents positive outcomes.

In this section, hypothesis testing is utilised on the same metric across different subsets of data, hence Bonferroni correction was applied to the $p$ value to give $p_{adj}$.

Figure 5.3A illustrates that for bomb kicks, there were increases in positive outcomes and decreases in negative outcomes as the relative kick value increased; however, there was not a significant difference in relative kicks between outcomes (H(2, 321) = 3.71, $p_{adj}$ = 1.00). In Figure 5.3B, box kicks appeared to have a different relationship, with positive and negative outcomes both decreasing as relative bomb kicks increased, with a noted increase in neutral outcomes. This difference in relative box kicks was significantly different between outcomes (H(2, 1473) = 143.88, $p_{adj}$ = .001). The Dunn test illustrated significant differences between neutral outcomes and both positive and negative outcomes (Appendix B.2).

Chip kicks (Figure 5.3C) appeared to have an unclear relationship with sequence outcome, with no steady change in outcomes (H(2, 288) = 9.37, $p_{adj}$ = .063). Cross-pitch kicks had an inconsistent relationship with sequence outcomes. There was an increase in positive outcomes as teams move from -1 to +1 but in between these values, the relationship is unclear (Figure 5.3D). When teams make an equal number of cross-pitch kicks, there was always a negative outcome for the team in possession at the end of the sequence. There was no significant difference between relative kicks in each outcome for cross pitch kicks (H(2, 119) = 5.89, $p_{adj}$ = .371).

Increased low kicks led to an increase in positive outcomes and a reduction in negatives with the exception of +2 relative low kicks (Figure 5.3E). There was a significant difference between relative kicks in each outcome (H(2, 605) = 12.22, $p_{adj}$ = .014). Dunn testing identified significant differences between positive and both neutral and negative outcomes (Appendix B.2). Territorial kicks had the clearest relationship with sequence outcome, with an increase in positive outcomes as more relative territorial kicks are made (Figure 5.3F). This increase was particularly noticeable as the kicks increased from -1 to 0 to +1, and confirmed by a significant difference in relative kicks between outcomes (H(2, 1409) = 38.46, $p_{adj}$ < .001). In this case, Dunn testing also identified significant differences between positive and both neutral and negative outcomes (Appendix B.2).

Touch kicks were not included in this analysis, given their outcome of reaching touch (as long as an error has not been made) is naturally neutral and other than the case of failure to meet touch, there are very few circumstances where multiple touch kicks would exist in one sequence hence calculating relative values does not add value to this chapter.

Differences between relative kicks and more detailed outcomes were analysed, for example, 51% of tries scored in kicking sequences came from sequences where the scoring team made +1 relative kick over their opposition, with 62% originating from a sequence with positive relative kicks overall (Figure 5.4). On the contrary, of tries conceded, 58% were conceded when a team had zero or fewer relative kicks than their opposition.

In terms of penalties, 37% of penalties won were awarded when a team made +1 relative kicks, compared to 40% when -1 were made. Conversely, only 26% of penalties conceded were conceded when a team made +1 relative kicks, compared to 40% when a team made -1 relative kicks (Figure 5.4).

When possession was gained by the kicking team, 46% of these gains occurred when a team had made +1 relative kicks. This was similar when possession was conceded, with 49% of possession losses occurring in +1 relative kicks (Figure 5.4). Neutral outcomes tended to be driven by +1 relative kicks, with 71% of kicks out of play and 68% of other neutral outcomes occurring when a team made +1 relative kicks (Figure 5.4).

Hypothesis testing identified a difference in relative kicks between the more detailed outcome responses ($H(7,3759) = 482.35$, $p < .001$). Dunn testing is available in Appendix B.2.

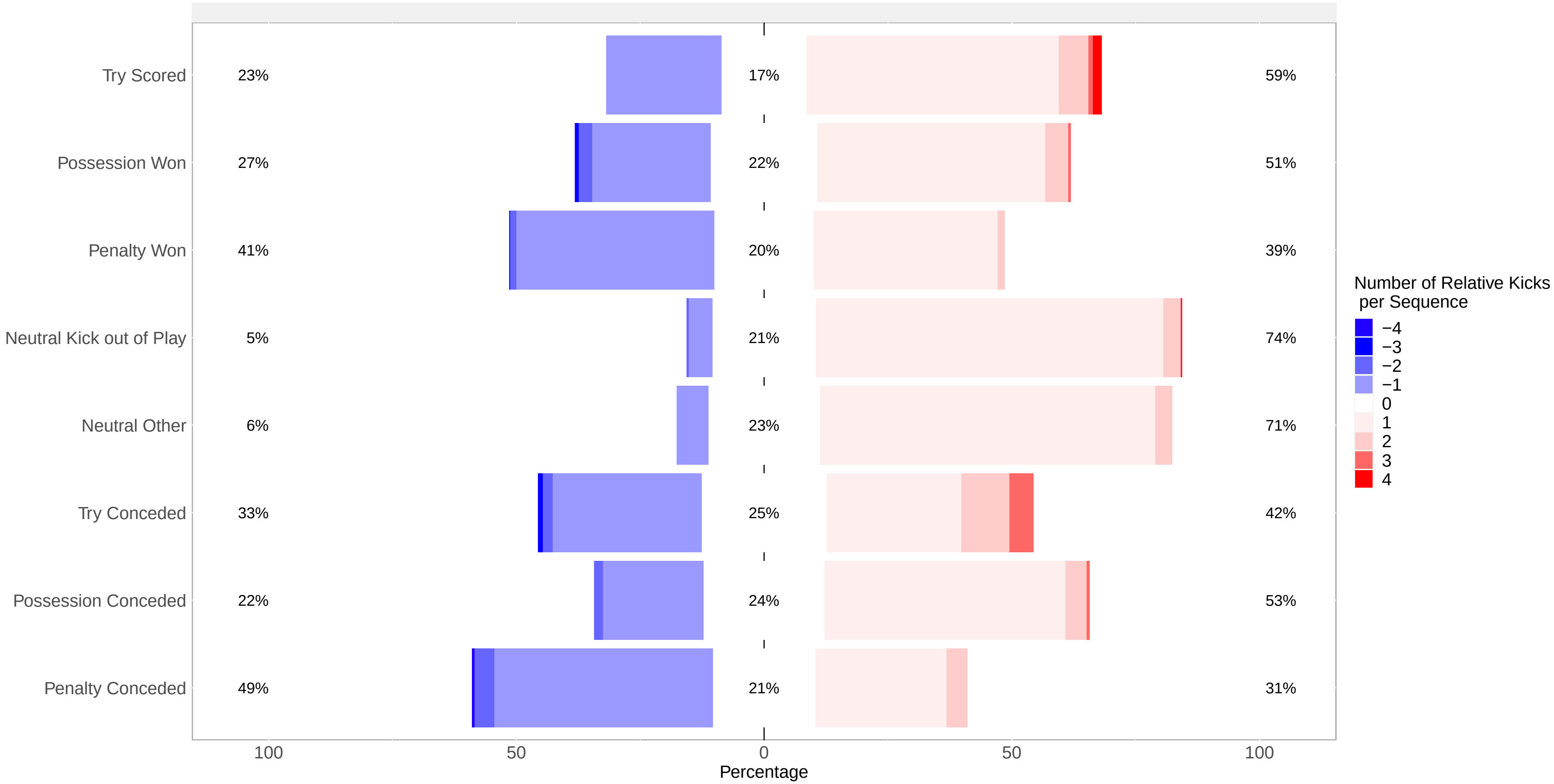



**Figure 5.4**
Figure illustrates the percentage of each detailed sequence outcome across the relative kicks for the reference team in the sequence. The $y$-axis displays the detailed outcomes, whilst the $x$-axis displays the percentage of sequence outcomes associated with negative, zero and positive relative kick values. The red scale highlights the positive relative kick values (1,2,3,4), white represents the zero relative kick values (0) and blue represents the negative kick values (-1,-2,-3,-4). As only one sequence contained -5 kicks, this has been omitted from the figure.

## 5.5 Discussion

The primary aim of this chapter was to understand the influence of relative kicks at a sequence level across matches, given the importance of kicking that was highlighted in Chapter 4. It was identified in Chapter 4 that kicking more than your opposition was associated with winning outcomes, hence it was important to understand this effect at the play-by-play level in order to provide more valuable applied insight. Results indicated that within the majority of sequences (53%), one team tended to make one more additional kick than the opposition team. This suggests that additional kicks are gained by teams across multiple sequences in a match. Most commonly, teams with possession when the sequence ends tended to have only made one kick during the sequences, suggesting that this kick either went into touch before the opposition could touch it or was contested by the kicking team to regain possession. The proportion plots (Figure 5.2) showed the association between increased relative kicks and a decrease in negative outcomes across sequences. It was also identified that the majority of tries scored in kicking sequences were scored in sequences with +1 relative kicks for the scoring team (51%).

Firstly, when total kicks for each team and relative kicks were calculated, there was a similar relationship as had been observed in Chapter 4 when comparing isolated and relative PIs across a whole match. Total kicks by the reference and opposition teams were skewed, with values of 1.3 and 1.5 respectively, demonstrating a positive skew to the data. Total kicks per sequence for both teams combined also had a skew (skewness = 2.4). When the data was expressed relative to the reference team, the distribution became more symmetric (skewness = -0.6). This suggests that this relative relationship between the two teams can be observed in match statistics at the sequence level as well as the match level, as identified in the previous chapter and other research (Bennett et al., 2019, 2020; Mosey & Mitchell, 2020). This allows the concept of relative values to be utilised at the sequence level, which may be much more manageable in terms of developing game tactics and messaging to players on field, as understanding what to do in the next sequence is simpler than planning across an entire match.

The highest proportion of relative kicks was +1 kicks per sequence (53%). Given that relative kicks were contextualised to the team in possession, this high density at positive one suggests that most commonly teams in possession at the end of the sequence had made one more kick than their opposition. It is important to note that this means they had possession at the end of the sequence, it does not mean that possession was maintained in the next sequence. However, this yields two sets of circumstances that lead to having possession at the end of the sequence given a kick was made: it either means the kick immediately went into touch, or the kick was regathered by the kicking team in some way during the sequence. This begins to demonstrate the impact of kicking, that it is possible that positive outcomes come from regathering possession or the gain in territory from kicking into touch. Chapter 4 demonstrated that if a team takes up to 10 more kicks than the opposition across a whole match, it can lead to an increase in the probability of winning. This chapter has confirmed that these additional kicks are likely built up over many sequences across the game, typically by gaining +1 across each of the sequences.

There was no clear relationship between outcomes and the total number of kicks taken by a team in the sequences (H(2, 3759) = 2.77, $p$ = .250). However, when the relative transformation was applied, a relationship was observed (H(2, 3759) = 389.2, $p$ < .001). It was clear that an increase in kicks led to an increase in neutral outcomes and a decrease in negative outcomes. This suggests that kicks into touch might be one way teams use kicks to their advantage. Neutral outcomes were included in this chapter as they form a large part of outcomes from kicking sequences and thus yielded additional insights around the possible benefit from additional kicking. However, some aspects of neutral outcomes are still open for interpretation and improvement, particularly with the understanding of the benefit given to each team in a neutral outcome. For example, a kick into touch may give a team territory but it also loses possession to the opposition, unless it is a 50:22 outcome (World-Rugby, 2021), with the latter coded as a positive outcome rather than neutral in this thesis. The decrease of both positive and negative outcomes when relative kicks increase is likely a symptom of less time with the ball in hand. This suggests that kicking is a low-risk, low-reward option at the sequence level: limiting risks of negative outcomes but limiting the positive outcomes too, albeit at a slightly lower rate (5% decrease in positive outcomes after one relative kick compared to a 9% in negative outcomes). However, this analysis focuses solely on sequences containing kicks, it may be that these kicks are pathways to additional sequences later on that allow teams to score points. In this case, it may be that the low reward from a kicking sequence can build up to a high reward sequence outcome in conjunction with other sequences. For example, a kick to touch may give a team the opportunity for a lineout steal in the opposition half.

Relative territorial kicks demonstrated a clear relationship with sequence outcomes (H(2, 1409) = 38.46, $p_{adj} < .001$) with an increase in relative kicks leading to an increase in positive outcomes, for example, 35% of sequences ended with a positive outcome for the reference team when they made -1 relative territorial kicks compared to 60% with +1 relative territorial kicks. This research corroborates with the previous hypothesis that ″winning″ rugby kicking battles leads to positives for the team who finish the battle. When teams have an additional territorial kick, they tend to have higher positive outcomes, this situation happens when either the kicking team start and finish the kicking battles, or makes the only territorial kick of the sequence. This suggests that teams should not only aim to start the kicking battles, but also finish them irrespective of which team started them. From a practical perspective, it is likely that this tactic allows the kicking team to either gain in territory or tactically by pressuring the catching team. This pressure may be explained by forcing the catching player to make an error, either in their catch, return kick, or preventing them from catching the ball at all. Analysis of the outcomes of multiple territorial kicks is required to understand this further, as well as an understanding of the spatiotemporal demands of these kicks, which may define how much pressure a team can put on a kick.

Similarly, relative low kicks also had a relationship with outcomes within sequences (H(2, 605) = 12.22, $p_{adj} = .014$). A different style of kick to territorial, these kicks tend to form more of an attacking approach and are often retained by the kicking team. It is therefore understandable that an increase in these kicks over the opposition leads to positive outcomes, with 45% of sequences ending positively when a team makes +1 relative low kicks, compared to only 30% when they make -1 relative low kicks. This is in contrast to what is achieved with the aforementioned territorial kicks. These kicks together reveal a larger picture of kicking tactics, with the concept of separate territorial and attacking kicking styles and tactics.

One further kick type had an obvious relationship with sequence outcome: box kicks (H(2, 1473) = 143.88, $p_{adj}$ = .001). This kick type had an increased percentage of neutral outcomes as the relative value increased, 50% when there were +1 relative box kicks compared to 16% when there were -1 relative box kicks. The increase in neutral outcomes does not intrinsically link to any change in success, but the decrease in positive and negative outcomes suggests another way in which kicks can be implemented to create success. These kicks are often taken in vulnerable positions (inside a team's own 22 m), to gain territory and remove the pressure of the opposition, therefore avoiding conceding points in this region. This is a relative way in which teams can create success in a match without directly scoring points, but by avoiding the opposition from scoring, therefore still contributing to relative points differences.

Other relative kicks, namely bomb, cross pitch and chip kicks all had unclear relationships with sequence outcome when analysed in this manner. This may be due to the number of sequences available where that contained these kicks (Figure 5.3). Furthermore, the latter two could be described as attacking kicks, therefore it is uncommon that the same kick type is repeated by both teams within one sequence compared to the other kick types. However, it is possible that their relationship with positive outcomes could be more thoroughly analysed in a different manner with some kick types combined or in a larger dataset, or perhaps through combining the data itself with video footage to understand the dynamic movement and field position of other players when these kicks are taken.

This type of study is novel in its area, and no similar research has been published in Rugby Union, Rugby League or Australian Football at the current time. XML data can be challenging to extract and analyse, which likely explains the lack of analysis in this field. Limited studies in rugby codes have used XML data for analysis, including Bunker et al. (2021) and Rennie et al. (2022). However, neither of these studies investigated kicking, and thus the findings in this chapter are highly novel. The current methodology gives a greater contextual understanding of kicking and sequence outcome than the aggregated match values given in the previous chapter and other research in this area.

## 5.6 Practical Applications

These results can be used in practice to develop kicking strategies within teams. This data suggests that there is a combination of possession-based and territorial kicking used to promote winning sequences across the match. The relative nature of kicking, given in the previous chapter, suggests that it is the act of increasing the likelihood of scoring as well as decreasing the likelihood of the opposition scoring that leads to success from kicking tactics. This chapter also promotes a similar message to Chapter 4 - that it is key for teams to out-kick their opponent not only on the match level but on a sequence level. This may be by taking an extra kick or even taking the only kick of the sequence.

## 5.7 Limitations

There are limitations within this chapter, firstly, the lack of field position given to the kicks. As this chapter investigated multiple kicks in each sequence, there was not scope to include field position in the data summation. Adding field position may give additional context to each individual kick and understanding as to what tactics can be used in which areas of the field.

Secondly, this chapter includes all sequences from 144 matches within the 2021/22 season, indicating that winning and losing teams will both be represented in this dataset. This is positive in some ways as it gives additional data, and it is true that winning and losing teams both have their own share of positive, neutral and negative outcomes within a single game. However, it may be beneficial to understand what kicking and its related sequence outcome presents as solely from winning or losing teams separately. This may help to understand factors that separate ″good″ performances and winning outcomes.

Finally, the lack of spatiotemporal data in this chapter limits what can be understood about kicking in terms of physical performance. One of the next steps of this research is therefore to build connections between tactical decisions and technical and physical performance, and this can be aided by the understanding of the spatiotemporal demands of kicking.

## 5.8 Conclusion

The current analysis aimed to understand how relative kicks impacted performance at the sequence level. It is clear that relative kicks are built across a match, with the most common value of relative kicks in a sequence being +1 relative kicks.

The importance of relative kicks was also highlighted in terms of sequence outcomes, with increased relative kicks leading to increased neutral outcomes, driven by kicks to touch, as well as decreased negative outcomes. This suggests that territory may be a very important part of kicking tactics. Outside of touch kicks, neutral outcomes were mainly driven by making one additional box kick, whereas additional territorial and low kicks were associated more with positive outcomes. Equally, it was found that the majority of tries scored in kicking sequences took place in a sequence where the reference team made one additional kick than their opposition (+1 relative kicks).

The next step in this area is to understand the difference in kicking between winning and losing teams, the direct outcome associated with these kicks, and consider some field context to further understand kicking tactics in different field positions. Equally, the understanding of spatiotemporal characteristics associated with these kicks may allow teams to tie in tactical decisions with technical and physical performance to build a plan to promote overall performance.

# 6 Are there differences in kicking tactics between winning and losing teams?

## 6.1 Abstract

**Background** Studies within Rugby Union have repeatedly identified kicking as a key indicator of success, yet no further analysis has been completed to quantify differences between kicking in winning and losing teams. While it has been demonstrated that out-kicking your opposition is strategically important, a greater contextual understanding is required to allow deployment of actionable interventions to promote improved outcomes.

**Aims** The aim of this chapter was to investigate whether differences exist in kicking tactics between winning and losing teams.

**Methods** Coded video analysis files were downloaded from 144 matches within the 2021/22 season of the United Rugby Championship. Sequences containing kicks were isolated and the kicks in each sequence were collected ($n$ = 6587). For each kick, the type was identified and allocated to one of five zones across the field. The proportion of kick type and kicks taken in each zone was recorded across the full dataset and then divided into winning and losing team kicks, according to match outcome. Single kick sequences were then isolated ($n$ = 2212) and the outcome score of each sequence was obtained based on the objective outcome previously used in this thesis and position on field. The Mann Whitney U test was utilised to compare outcome score between winning and losing teams across different kicks and zones.

**Results** Winning teams kicked more than losing teams in all zones of the field and all kick types. However, both teams had a similar distribution across kick types ($\chi^2$(6, 6403) = 3.95, $p$ = .683) and zones ($\chi^2$(4, 6403) = 1.72, $p$ = .786), proportional to their total number of kicks. Although there was no overall difference in outcome score between winning and losing teams (U = 629602, $p$ = .054), there was a significant difference in outcome score when teams utilised kicks in the red zone of the field (U = 1716, $p_{adj}$ = .030). Post hoc analysis revealed that winning teams scored a higher percentage of tries in positive kicking sequences (13% of

positive outcomes compared to 8% in losing teams) and conceded a lower percentage of tries in negative kicking sequences (4% compared to 14% in losing teams).

**Conclusion** Kicking tactics across winning and losing teams are similar, except in the red zone where winning teams excel in gaining positive sequence outcomes. This suggests that attacking kicking may be beneficial to promote success at the sequence level. However, the majority of kicks taken in this dataset were kicked from a team's own half and utilising box, territorial and touch kicks, suggesting that territory is also a key kicking concept in both winning and losing teams.

## 6.2 Introduction

Based on the results of Chapters 4 and 5, kicking has been identified as a key area of interest within rugby. Chapter 4 identified key PIs associated with success, utilising methods in data reduction to allow simplified monitoring of PIs in a practical environment. The chapter identified five key PIs associated with success in the URC, with relative kicking highlighted, signifying winning teams benefit from kicking more than their opposition. Kicking has also been identified as an important indicator of match outcome in other literature, including in other competitions such as at the international level and in Premiership Rugby (Bennett et al., 2019, 2020; M. T. Hughes et al., 2012). Chapter 4 corroborated results from literature, identifying that winning teams ″outkick″ their opposition (Bennett et al., 2019, 2020). Despite being commonly identified across different competitions within rugby, kicking has not garnered further detailed research within the literature into performance. For example, whilst investigating kicking injuries, Lazarczuk et al. (2020) reported the kicking characteristics in English Competitions, identifying a baseline understanding of the spread of kick types across many matches (Lazarczuk et al., 2020). However, no mechanistic link to performance was investigated within this study.

From the five key PIs, metres made and clean breaks are intuitive attacking metrics, and turnovers conceded and scrum penalties are clear areas of error. Kicking is the final PI and its link to success is not as intuitive. Chapter 5 examined these kicks across the sequence level; that is, a sequence of actions between the ball going into play and then out of play. These results identified that additional kicks at the sequence level can increase neutral sequence outcomes, as well as decrease negative sequence outcomes. It was also identified that combinations of different kick types within sequences can increase positive outcomes. However, there is a limited body of literature on this subject to corroborate results, as both kicking and sequence analysis have not yet garnered meaningful attention from researchers. Equally, there is a deficiency in analysis into the further details of the match rather than solely investigating match aggregated statistics. The limited research into the sequence outcomes has isolated scoring sequence outcomes and analysed actions that have taken place in those sequences, identifying that regained kicks in play were related to scoring outcomes (Bunker et al., 2021).

As well as a lack of research investigating kicking, both at the match level and in the deeper sequence level, there is a lack of understanding as to why kicking is important to winners and how it can be tactically manipulated for success. In previous research (Chapter 4, Bennett et al. (2019), Bennett et al. (2020), Mosey and Mitchell (2020)), kicking more frequently has been identified as a winning strategy at the match level, and equally kicking in sequences can decrease negative outcomes, as well as increase neutral outcomes (Chapter 5). What is unknown is whether winning teams benefit solely from their increased kicking or have decreased negative outcomes and possibly increased positive and neutral outcomes from kicking sequences. In essence, do winning teams just kick more or do they kick ″better″, by implementing different kick types, using different areas of the field and achieving different sequence outcomes?

Given this, the current chapter aims to investigate whether differences exist in kicking tactics between winning and losing teams, this will be directed by the following research questions:

- What are the frequencies of different kick types and zones used in a season of the URC?
- What are the differences in the frequency of kick types and zones between winning and losing teams?
- Do winning and losing teams display differences in sequence outcomes from single kick sequences?

## 6.3 Methods

The dataset of kicks from Chapter 5 was utilised initially ($n$ = 6587) and when statistical methods were employed comparing sequence outcomes, only kicks belonging to a single kick sequence were analysed to ensure the independence of observations ($n$ = 2212).

To analyse different areas in which kicks were used, field zones as described in the general methods were utilised in this chapter. These zones were colour-coded as follows: Red, Silver, Gold, Blue and Green.

### 6.3.1 Sequence Outcome

Sequence outcomes were grouped as positive, neutral or negative based on detailed descriptions in the general methods. In this chapter, this outcome was contextualised to the team who made the single kick in the single kick sequences rather than the team in possession as within the previous chapter. However, this outcome group does not consider that field position could be important, particularly to neutral outcomes which are predominantly driven by kicks into touch (93% of neutral outcomes originated from a kick to touch in this dataset). The next stage of this analysis involved applying a numerical score to the outcomes to address some of these limitations.

Within this chapter, positive outcomes were assigned the value of 1 and negative outcomes were assigned the value of -1. Neutral outcomes were scaled based on pitch position in relation to the opposition try line and as most sequence outcomes in the neutral category were caused by kicks to touch (93%), the horizontal (i.e. portions of the pitch from one sideline to the other) pitch position was not considered within this analysis. If a neutral outcome ended a sequence on a team's own try line, it would be given the value of -1 and if it was on the opposition's try line, that would be attributed the value of 1 (and on the halfway line it would be attributed a value of 0). The relationship between these two points was linear with the value of the outcome increasing from -1 up to 1 as the sequence end co-ordinate advances forward along the field towards the opposition try line. Therefore, neutral outcomes become increasingly positive as a sequence ends in the opposition half, and increasingly negative as it ends further back into their own half. The exact values of positive, neutral and negative outcomes at each point of the field are displayed in Figure 6.1. This allowed the comparison of an outcome score across groups of kick types or kicks in certain zones of the field.

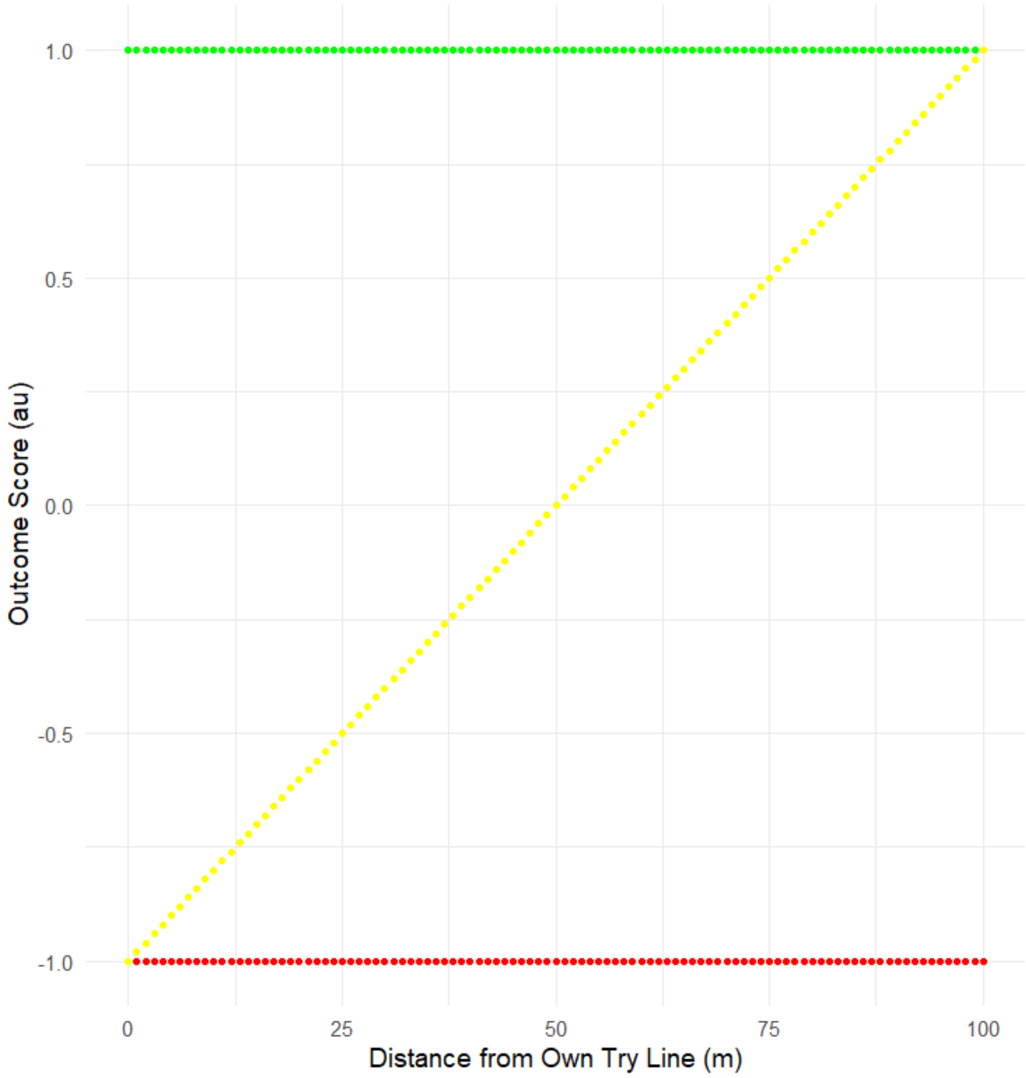



**Figure 6.1**
Scatter plot demonstrating the outcome score for positive, neutral and negative values, in green, yellow and red respectively. The $y$-axis demonstrates the outcome score, based on the $x$-axis, depicting the distance from a team's own try line. This figure highlights that a positive or negative value stays consistent across the field, at an outcome score of +1 or -1 respectively. The neutral outcomes outcome score increases as a team moves closer to their opposition's try line, with negative values til the halfway line (50 m) and positive values beyond this towards the opposition's try line.

### 6.3.2 Statistical Methods

Within the current chapter, the Chi-Squared goodness of fit test was applied to compare the frequencies of each kick type and repeated to compare the frequencies of kicks in different zones. The null hypothesis was that the number of kicks in each kick type or zone was evenly distributed. The Chi-Squared test of independence was then utilised to evaluate whether an association between kick types and zones could be identified. The Chi-Squared test of independence was also applied to compare whether there was a difference between kick types utilised between winning and losing teams. Similarly, this was repeated to compare kicks in zones between winning and losing teams. The Cochran-Mantel-Haenszel test was applied to test whether there was an association with kick types and kick zones, whilst correcting for winning and losing status.

The Mann Whitney U test was applied to compare outcome scores between winning and losing teams. This was tested across all kicks, and then repeated on subsets of the kicks, including each kick type and kick zone. Due to multiple testing, Bonferroni's correction was utilised to give an adjusted $p$ value ($p_{adj}$). The Dunn test was utilised post-hoc to investigate comparisons.

Finally, decision trees were created post hoc to compare more detailed sequence outcomes from the positive, neutral and negative sequences for both winning and losing teams.

## 6.4 Results

### 6.4.1 Frequency Analysis of All Kicks

In the initial analysis of the frequency of kicks, 6587 kicks were summarised and subject to hypothesis testing. The Chi-Squared goodness of fit test highlighted that the kicks were not evenly distributed between zones ($\chi^2(4,6587) = 2849.70$, $p < .001$). The majority of kicks took place within a team's own half, with 34% of kicks taken from the green zone and a further 33% taken in the blue zone (Table 6.1). Within the gold zone, the centre of the field, 23% of kicks were taken. A small number of kicks were taken in the opposition half, with 7% and 3% of all kicks taken in the silver and red zones respectively.

Blue and gold zone kicks were more likely to be part of multi-kick sequences, with only 21% and 26% recorded in single kick sequences (Table 6.1). Comparatively, green and silver zone kicks had a higher percentage of kicks belonging to single kick sequences (49% and 44% respectively). The majority of red zone kicks were in a single kick sequence (65%).

**Table 6.1**
Frequency (n) and percentage (%) of kicks taken in each of the five field zones within the dataset, the final column denotes what percentage (%) of kicks in each zone belonged to a single kick sequence.

| Zone Name | Number of Kicks | Percentage of Total Kicks (%) | Percentage in a Single Kick Sequence (%) |
|---|---|---|---|
| Red | 168 | 3 | 65 |
| Silver | 455 | 7 | 44 |
| Gold | 1531 | 23 | 26 |
| Blue | 2172 | 33 | 21 |
| Green | 2261 | 34 | 49 |

The Chi-Squared goodness of fit test also highlighted that the kicks were not evenly distributed between kick types ($\chi^2(6{,}6587) = 3948.70$, $p < .001$). Territorial kicks were the largest proportion of kicks in the dataset, forming 34% of all kicks that were recorded, followed by box kicks and touch kicks at 27% and 18% respectively (Table 6.2). The dataset also included low kicks, contributing to 10% of the kicks, and chips and bombs both accounting for 5% each. Cross pitch was the smallest group at 2% of all kicks.

Bomb and territorial kicks had a low proportion of kicks belonging to a single kick sequence (25% and 17%, respectively), whereas touch kick and cross pitch kicks had a higher proportion, with the majority of kicks belonging to single kick sequences (55% and 57% respectively)(Table 6.2). The proportions of box, low and chip kicks contained in a single kick sequence were 42%, 36% and 32% respectively.

**Table 6.2**
Frequency (n) and percentage (%) of kick types, the final column denotes what percentage (%) of each kick type belonged to a single kick sequence.

| Kick Type | Number of Kicks | Percentage of Total Kicks (%) | Percentage in a Single Kick Sequence (%) |
|---|---|---|---|
| Bomb | 341 | 5 | 25 |
| Box | 1765 | 27 | 42 |
| Chip | 298 | 5 | 32 |
| Cross Pitch | 120 | 2 | 57 |
| Low | 665 | 10 | 36 |
| Territorial | 2209 | 34 | 17 |
| Touch Kick | 1189 | 18 | 55 |

The Chi-Squared test of independence demonstrated an association between kick type and zone ($\chi^2$(24,6587) = 3097.70, $p$ < .001). Chip, cross pitch and low kicks tend to be predominately taken in the red and silver zones, meanwhile, box, territorial and touch kicks are primarily taken in the green and blue zones (Table 6.3). A summary of the frequency of kick types taken in each zone is displayed in Table 6.3.

**Table 6.3**
Table of the frequency (n) of each kick types taken in each of the five field zones.

| | | Kick Zone | | | | |
|---|---|---|---|---|---|---|
| | | Red | Silver | Gold | Blue | Green |
| Kick Type | Bomb | 0 | 10 | 160 | 150 | 21 |
| | Box | 7 | 27 | 396 | 708 | 627 |
| | Chip | 26 | 74 | 130 | 52 | 16 |
| | Cross Pitch | 29 | 33 | 29 | 19 | 10 |
| | Low | 91 | 222 | 230 | 87 | 35 |
| | Territorial | 9 | 60 | 426 | 981 | 733 |
| | Touch Kick | 6 | 29 | 160 | 175 | 819 |

### 6.4.2 Frequency Analysis Comparing Winners and Losers

In this section, there were 6403 kicks analysed as 184 were removed due to occurring in a match that ended in a draw ($n$ = 3). The remaining kicks were further classified based on whether they were taken by the winner or loser of the match in question.

There was not a significant relationship between the kick zones used between winning and losing teams ($\chi^2(4, 6403) = 1.72$, $p = .786$). Despite no clear differences between the zones used, winning teams used more kicks than losing teams in all zones (Table 6.4).

**Table 6.4**
Frequency (n) and percentage (%) of kicks utilised in the five zones by winning teams and losing teams.

| Zone Name | Number of Winning Team Kicks | Percentage of Total Winning Team Kicks (%) | Number of Losing Team Kicks | Percentage of Total Losing Team Kicks (%) |
|---|---|---|---|---|
| Red | 90 | 3 | 74 | 2 |
| Silver | 247 | 7 | 198 | 7 |
| Gold | 794 | 23 | 689 | 23 |
| Blue | 1123 | 33 | 989 | 33 |
| Green | 1153 | 34 | 1046 | 35 |

Similarly, there was not a significant relationship between kick types used between winning and losing teams ($\chi^2(6, 6403) = 3.95$, $p = .683$). Winning teams used more kicks than losing teams across all kick types (Table 6.5).

**Table 6.5**
Frequency (n) and percentage (%) of kick types utilised by winning teams and losing teams.

| Kick Type | Number of Winning Team Kicks | Percentage of Total Winning Team Kicks (%) | Number of Losing Team Kicks | Percentage of Total Losing Team Kicks (%) |
|---|---|---|---|---|
| Bomb | 169 | 5 | 160 | 5 |
| Box | 942 | 28 | 789 | 26 |
| Chip | 149 | 5 | 139 | 5 |
| Cross Pitch | 69 | 2 | 50 | 2 |
| Low | 354 | 10 | 298 | 10 |
| Territorial | 1111 | 33 | 1016 | 34 |
| Touch | 613 | 18 | 544 | 18 |

There was a significant relationship between the kick types and zones even when this was corrected for winning and losing status ($\chi^2(24, 6403) = 3003.00$, $p < .001$).

### 6.4.3 Sequence Analysis of Winners and Losers

In this section, only kicks belonging to single kick sequences were analysed to maintain the independence of observations of sequence outcomes. This reduced the dataset to 2212 kicks.

There was no significant difference in the outcome score between winning and losing teams overall (U = 629602, $p$ = .054)(Figure 6.2).

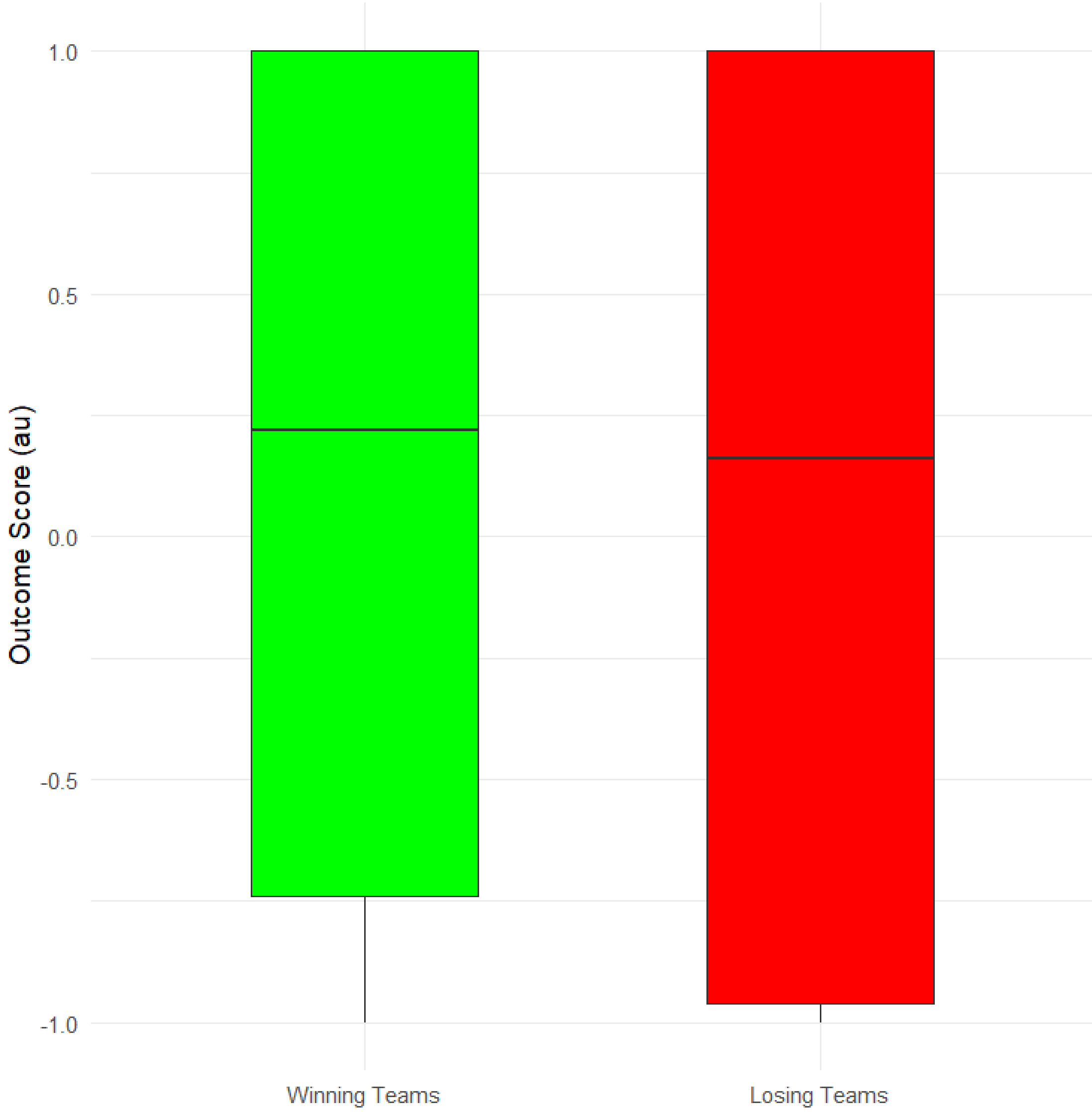



**Figure 6.2**
Box plot illustrating the distribution of outcome score across winning teams (green) and losing teams (red). The box plot displays a similarity in the median and IQR of both groups.

A significant difference in outcome scores between winning and losing teams was identified in sequences containing red kicks only (U = 1716, $p_{adj}$ = .030). There were no significant differences in outcome scores between winning and losing teams identified in any kick type.

A full summary of hypothesis testing can be found in the Appendix C.1.

The decision tree demonstrated a higher probability of positive outcomes for single kick sequences in winning teams compared to losing teams (34% compared to 29%) and lower negative outcomes (23% compared to 25%) (Figure 6.3). This figure also highlights differences within positive outcomes between teams, with 13% of positive outcomes in winning teams consisting of a try being scored, compared to only 8% in losing teams. Equally, negative outcomes contained a lower proportion of tries conceded in winning teams compared to losing teams (4% to 14%).

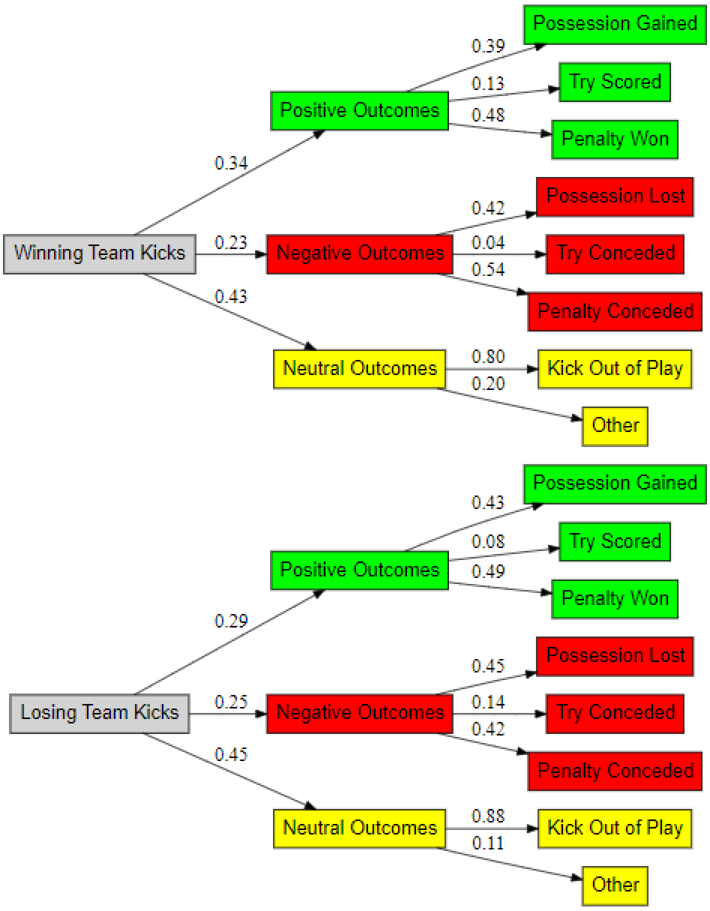



**Figure 6.3**
A visual representation of the sequence outcomes of single kick sequences for kicking teams, for both winning and losing teams. At each node, the values of the branches represent the probability of sequences that reach each outcome, with these proportions summing to 1. The top decision tree represents the probability of outcomes for the winning teams, whereas the bottom represents the probability of outcomes of losing teams.

## 6.5 Discussion

The primary aims of this chapter were to investigate whether differences exist in kicking tactics between winning and losing teams by evaluating the frequency of different kick types and zones used in a season of the URC and comparing these frequencies between winning and losing teams. A further aim was to compare differences in outcomes of single kick sequences between winning and losing teams. Results have identified that the number of kick types and zones used in the URC is not balanced, with teams performing more territorial, box and touch kicks (Table 6.2) and primarily taking kicks from inside their own half, in the green and blue zones (Table 6.1). A significant association between kick type and zone was also identified ($\chi^2$(24,6587) = 3097.70, $p$ < .001), implying that teams favour certain kick types in particular areas of the field, even when correcting for winning and losing status ($\chi^2$(24, 6403) = 3003.0, $p$ < .001). This chapter also identified that kick types ($\chi^2$(6, 6403) = 3.953, $p$ = .683) and zones ($\chi^2$(4, 6403) = 1.7247, $p$ = .786) utilised did not differ significantly between winning and losing teams. Finally, analysis of sequence outcome scores did not demonstrate an overall significant difference between winning and losing teams (U= 629602, $p$ = .054), but a significant difference was exhibited when red zone kicking sequences were compared individually (U= 1716, $p_{adj}$ = .030). Post hoc analysis identified that positive kicking sequence outcomes for winning teams tended to have a higher proportion of tries scored compared to losing teams, whilst negative kicking sequence outcomes had a lower proportion of tries conceded than losing teams (Figure 6.3).

This thesis identified that kicks were not taken equally across the entire field of play. The majority of kicks tended to be taken in a team's own half, with the proportion of kicks decreasing as a team advances towards their opposition try line. Teams within the URC favoured kicks in the green and blue zones (34% and 33% of all kicks, respectively), but it was identified that these kicks may have different purposes given their link to single kick sequences. Green zone kicks tended to belong to single kick sequences, and were often kicked off the field of play (48% of all green zone kick outcomes). This suggests that teams may primarily utilise green kicks to relieve pressure by kicking into touch, hence forcing a lineout further down the field of play. Given the green zone's inclusion of a team's own try line, it may be that these kicks may help teams avoid conceding penalties or even tries in this vulnerable area of the field. On the contrary, blue zone kicks were more likely to be part of a multi-kick sequence (79% of kicks), suggesting they form either a team's multi-kick tactic or a kick exchange with the opposition team, given that 74% were caught by the opposition. Equally, within the rules of rugby, if these kicks go directly into touch, it would be considered an error and the lineout would be given at the starting point of the kick. However, both zones appear part of a larger kicking strategy to gain territory by either kicking the ball in or out of play.

The gold zone appears to be a transition area in the field, where the number of kicks begins to decrease (23% of all kicks) but kicks tend to still form a multi-kick sequence (26%). Given that this zone position is in the centre of the field and that 74% of kicks were in a sequence of kicks, it appears likely that kick exchanges still occurred in this area of the field. The red and silver zones form a much smaller proportion of kicks taken, at 3% and 7% respectively. These kicks are more likely to form part of single kick sequences, which could suggest, given their proximity to an opposition try line, that they are utilised as attacking-style kicks.

Kick types were not performed equally within this dataset, with territorial, box and touch kicks comprising a large proportion of the dataset (34%, 27%, 18% respectively). Territorial kicks are longer distance kicks, intending to gain territory but stay within the field of play (Table 3.4). Touch kicks have a similar purpose but with the intention of forcing the ball out of the field of play, triggering a lineout (Table 3.4). The dominance of these kick types has been corroborated in research among players competing in both the English Premiership or internationally for England (Lazarczuk et al., 2020), in which researchers identified ″distance″ punts and box kicks as the largest groups of the kicks analysed, at approximately 30% and 18% respectively. This study did not separate touch kicks, so it is likely that many of the ″distance″ punts and box kicks went into touch.

Given the high proportion of touch kicks belonging to single kick sequences, it may be that, similar to green zone kicks, these are used to relieve pressure or gain territory downfield. Box kicks also had a high proportion of kicks in single kick sequences, implying that they are used similarly. They are often used to clear touch within the green zone, making up 69 % of kicks taken in this zone in the current chapter. Territorial kicks had a low proportion of kicks in single kick sequences indicating that these kicks form part of larger kicking exchanges. This could be the speculated ″kicking battles″ that have been alluded to in Chapters 3 and 4, where teams perform multiple kicks to each other within a period of play.

The smaller groups of kicks contained more ″attacking style″ kicks, including chip, cross pitch and low. Parallels can be identified comparing these kick types with Lazarczuk et al, with chip kicks featuring in the results and bomb and low corresponding to ″hang chase″ and ″ground kick″ respectively. Cross pitch kicks are not given in this study, instead they are grouped with chip kicks as a ″kick pass″. A similar proportion of each kick type was identified in the English Premiership and at the international level as was identified within this chapter (Lazarczuk et al., 2020).

Unsurprisingly, there are significant associations between kick types and zones given the results identifying the dominant kick types and zones alluded to in this discussion. There are clear similarities seen in the objective of certain kick types and the zones of the field, namely the use of more common kicks, such as territorial, touch and box kicks in commonly used areas of the field, such as the green and blue zones. This is driven both by the limitations of the kick used and the intention of its use. For example, a team aiming for a territorial gain are likely to do this in their own half rather than in their opposition half. Equally, low and chip kicks are likely to be shorter kicks or close to the ground by definition (Table 3.4), so are unlikely to be as effective as attacking measures when a team is still in their own half. However, these results do not show a single kick type is dedicated to a specific area of the field, identifying that teams have different kicking options in each area.

With a kicking identity developed across the game, it is key to understand whether this differs between winning and losing teams. Analysing differences between winning and losing teams is not a new concept within rugby. It has been commonly researched in multiple competitions (Colomer et al., 2020). Given this, is it intuitive that kicking should also be compared between winning and losing teams to interpret any differences. This chapter identified that there were no significant associations between the zones of the field used to kick and winning and losing. This suggests that despite winning teams completing additional kicks across the field, they do not favour a particular area of the field. This is contrary to what has been reported previously, where winning teams kicked a higher proportion of their kicks in their opposition 22-50 (M. T. Hughes et al., 2012) in international rugby. This is a similar zone of the field to the gold and silver zone described in this current chapter. M. T. Hughes et al. (2012) research was completed on data from the 2011 Rugby World Cup, hence it may be that the time between that competition and the current chapter's data may have led to differences, as kicking has increased over time (McCormick, 2019). Equally, this thesis analysed club level data, meanwhile M. T. Hughes et al. (2012) analysed data from the international level, this could also explain differences in results.

Neither did this chapter identify any key differences between the kick types used by winning and losing teams within the URC, in contrast with what has been reported within the literature. Vaz et al. (2011) identified that touch kicks were higher in winning teams compared to losing teams within World Cup, Six Nations and Super 12 close games. However, Vaz et al. (2011) did not report other kick types, so it is feasible that the exclusion of other kick types may have obscured the additional kicks within these matches. Equally, the study solely analysed close games which may cause differences to the results presented within this thesis. Incorporating the lack of association illustrated between both kick types and the zone used between winning and losing teams suggests that the main driver of success is the increase in kicks, regardless of where they are taken or what type of kick is used. Furthermore, significant associations between kick type and zone were identified even when winning and losing status was considered as a confounding factor. This again demonstrates that the relationship between different kick types and zones can be identified in winning and losing teams. It may be a consistent kicking strategy across the field and kick types are more important to gain success at both the match and sequence level than a specific kick tactic.

Given the lack of discrepancy in kicking characteristics, such as zone and kick type, between winning and losing teams, intuitively, the outcome of kicking becomes an area of interest. However, results from the current chapter failed to identify a significant difference in overall sequence outcome scores between winning and losing teams. This would suggest that winning teams do not necessarily have better outcomes from kicking, but they may utilise kicking more often within a match.

The red zone appears to be an area of importance in terms of kicking, given that it was the only category (for either zone or kick type) that recorded a significant difference in outcome score between winning and losing teams. Winning teams had improved outcomes when they kicked within the red zone, compared to losing teams. The literature has identified the red zone as a key area of interest within winning teams, with red-zone entries and conversion previously highlighted as indicators of successful teams (M. T. Hughes et al., 2012). The latter refers to how often a team scores compared to their number of red zone entries. This suggests that the actions in this zone are considered highly important given the proximity to the opposition's try line, which links actions to scoring opportunities. Kicking in this zone could be considered high risk but Stanhope and Hughes (1997) suggest that kicking here may allow the development of an attacking play.

Scoring opportunities, and inversely the possibility of conceding points are a large part of what drives success in this zone of the field and beyond. The decision trees within this chapter highlighted that winning teams not only have a higher probability of positive outcomes compared to losing teams (34%, compared to 29%), but a higher probability of try scoring given a positive outcome has taken place (13% compared to 8%, Figure 6.3). Whilst this is intuitive and has been reported in the literature (Ortega et al., 2009), it has not been identified in kicking sequences in isolation previously.

This chapter employed a new dataset and recognised statistical techniques to provide a novel and more detailed understanding of the characteristics of kicking across a season of the URC. It has also added further research into sequence outcomes within rugby like Bunker et al. (2021) and Watson et al. (2020) have previously analysed within the top flight of Japanese rugby and at the international level too. The dataset from this thesis is complex and has the potential to provide insights beyond what has been reported in this chapter and the previous (Chapter 5). There are multiple opportunities to broaden this work through extending this analysis to multi-kick sequences, or through examining the data from a physical performance perspective. The latter would allow the results from this chapter and the previous chapter, which may be more aligned with technical coaches and analysts, to be linked with the physical performance considerations. This may support practical applications from strength and conditioning coaches' perspectives, by understanding what the physical requirements of kicking are, from the point of view of the collecting or supporting players. This, in turn, may influence decisions in programming to support tactical decisions surrounding kicking in game.

## 6.6 Practical Applications

This research provides insight into the kicking load both across the field and across different kick types. Practitioners can use the initial frequency analysis to understand what the kicking demands are across the field and prepare appropriately for what is required from their players.

Results provided in this chapter have identified again that kicking more than your opposition is key, regardless of the zone or kick type used. This lack of distinct identity between winning and losing kicking can be viewed as a positive for practitioners considering improving their approaches to kicking. Teams may not need to drastically change their kicking tactics, but just increase their kicking in the strategy they already use across the field.

Red zone kicking strategies may be an area of development within teams, given their importance in this chapter. Gaining better outcomes within this zone may be a measure of a team's ability to make better decisions under pressure and fatigue, and to execute them accurately. Practitioners could identify opportunities to develop these skills in high-pressure or fatigued scenarios within the training week in an attempt to improve outcomes on match days.

Furthermore, practitioners may want to apply both the data collation and statistical methods employed by this chapter on their data to find more personalised insights into kick type preference and the kicking distribution of their own squad, as well as their outcome scores. This may be applied across a season, as has been completed in this current chapter, or at a micro level to identify key matches of interest for their team.

## 6.7 Limitations

Within the study design of this chapter, there are some key limitations to the results reported. Firstly, due to statistical requirements, the use of solely single kick sequences limits what can be discovered from this data. Although many kick sequences contain only one kick, these sequences do not show the full breadth of how kicking is utilised in the game. Further analysis of this data, particularly from a sequential analysis perspective, may benefit researchers and practitioners in terms of reaching a more dynamic understanding of the game. This may be especially useful in determining a greater understanding of kick exchanges between teams and how they are used within the game.

This chapter employed data from one data provider, which may not be aligned with other providers within the sport. It is important that when applying these results, care is taken if practitioners are using video analysis from other sources, particularly regarding kick and zone descriptions, as differences in categorisation have been identified in this chapter when comparing to Lazarczuk et al. (2020). Equally, the general methods identified some discrepancies with the x and y coordinates within this dataset. Despite the majority of kick coordinates being within 2 m of the original data, this could still impact the zone in which the kicks are categorised. However, given the zones are based upon pitch lines, visually this may be easier to categorise compared to kicks in areas of the field with no pitch markings. When the validity data was zoned, 4.6% of the tested kicks changed zone compared to the original zone given.

Another key limitation is the lack of data regarding the flight of the ball within each kick, as this chapter does not consider the speed and distance of the kick, which may also impact its success. Future research could aim to analyse this to understand its implication on the practical rugby environment, this would allow the extension of this performance analysis to a physical profiling and conditioning perspective.

## 6.8 Conclusion

This chapter aimed to evaluate the frequency of different kick types and zones across a season of the URC, as well as compare differences in kicking between winning and losing teams. Results identified that kicks were not evenly distributed across the field of play, with the majority of kicks taking place within a team's own half. Equally, kick types used within the season were not balanced, with territorial, box and touch kicks having higher proportions compared to bomb, chip, cross pitch and low kicks. Winning and losing teams did not differ in terms of kick types or zones used, and only had a significant difference in sequence outcome score when kicks were used within the red zone of the field. Decision trees identified that, in single kick sequences, winning teams' positive outcomes contained higher rates of tries scored and their negative outcomes had lower tries conceded, in comparison to losing teams.

In a practical environment, these results can be used to drive understanding into kicking load within a standard rugby season and scaled down to be understood match by match. Practitioners may want to use the recognition of the importance of the red zone to drive kicking strategies within this area as well as increase drills focussing on working under pressure or fatigue. This methodology can also be applied to new data to allow teams independence in understanding their own kicking strategies.

The next step in this area is to understand the physical demands that are associated with these kicks and how teams can prepare both tactically and within strength and conditioning programmes to perform these kicks successfully, particularly from the point of view of the players chasing kicks. This can be analysed by understanding the movement of the ball during these kicks and interpreting how other players or the kicker react.

# 7 What are the spatiotemporal characteristics of kicking?

## 7.1 Abstract

**Background** Kicking is a key part of modern rugby union, with outkicking your opposition identified as an indicator of successful match and sequence outcomes. Studies have reported the importance of kicking in many different leagues, levels and in both sexes, but there is limited research into the spatiotemporal demands of kicking and what physical requirements are needed to support kicking strategies.

**Aims** The aim of this chapter was to assess the spatiotemporal characteristics of kicks to inform the physical demands of a successful kick chase.

**Methods** Coded video analysis files were downloaded from 144 matches within the 2021/22 season of the United Rugby Championship. All kicks from hand were collated from these matches, and after data cleansing, 4443 kicks were analysed. The distance of the kick and time to the collection were measured and used to calculate the average speed. Descriptive statistics on these metrics were reported for kick types, kicks in different zones, different kick outcomes and field circumstances and the Kruskal Wallis test was used to compare differences. K-Means clustering was then used to cluster kicks based on their distance and collection time.

**Results** Mean kick distance for different zones of the field and collection times ranged from 19.8-44.1 m and 2.4-4.2 seconds respectively. Mean kick distance by type ranged from 22.8-51.4 m, with collection time ranging from 2.9-4.4 seconds. Distances and collection times also varied between different kicking outcomes and field circumstances. In clustering analysis, four was the optimum number of clusters. The cluster centres were (21.0 m, 2.29 s), (25.8 m, 4.23 s), (57.5 m, 6.19 s), and (48.9 m, 3.70 s).

**Conclusion** These differences highlighted that there is a divide between long kicks (which could be described as territorial), and shorter kicks (described as possible attacking or

contestable kicks). Outcomes tended to match this, with balls caught by the opposition reporting higher mean distances, compared to those caught by the kicking team. Clustering analysis identified four main clusters. Two of these clusters had higher mean distances: one with a higher mean collection time and one with a lower mean collection time. The other two were noted by lower distances, again with one cluster with a higher mean collection time and one with a lower mean collection time. This suggests that kicks can be split into four key groups, ″fast″ and ″slow″ territorial kicks and ″fast″ and ″slow″ contestable kicks.

## 7.2 Introduction

Kicking has been repeatedly identified as important to winning match outcomes within literature (Bennett et al., 2019, 2020; M. T. Hughes et al., 2012). Studies have identified relationships between both kicking more (M. T. Hughes et al., 2012) and out-kicking your opposition (Bennett et al., 2019, 2020), and winning match outcomes across multiple competitions. This has been corroborated within Chapters 4 and 5 of the current thesis, with the latter also confirming that similar relationships occur at the sequence level, that is, periods where the ball goes into play until the referee blows his whistle or the ball goes out of play. Additionally, Chapter 6 quantified that there were minimal differences between winning and losing teams' kicking strategies, suggesting that additional kicks are the leading cause of increased success.

Overall, previous chapters have reinforced that kicking is important within the URC, both at the match and sequence level, and investigated the differences between winning and losing strategies across kick types and zones, which provides an understanding of match performance and overall tactical strategies. Equally, sequence analysis also supports on-field decision-making and can assist with the development of drills within training to understand certain on-field scenarios. Currently, there is no analysis into the physical and spatiotemporal requirements of supporting kicking strategies. Given this, the next step of the current thesis was to understand how the analysis of spatiotemporal data from kicking in game can benefit practitioners in terms of informing tactical and physical preparation strategies, by understanding the field position required to support certain kicks and the requirements of supporting players during kicking to be able to contest a kick.

Within rugby, there have been relationships established between physical testing metrics and key performance indicators (Cunningham et al., 2018; Smart et al., 2011); however, this research did not include kicks from hand, suggesting a similar relationship could be established between kicking and physical performance. Increasing kicking across the game may lead to changes in physical demands from the players both taking the kicks and those supporting the following plays on the field, hence having a physical impact across a team.

There has been extensive research into the physical demands of rugby, predominantly through GPS metrics. Studies have identified differences between forwards and backs, as well as differences in training and match day (Roberts et al., 2008; Tee et al., 2016). There is yet to be any research identifying the demands of kicking on the supporting players, with the majority of literature in kicking aiming to understand the biomechanics of the kicking action (Bezodis et al., 2017; Green et al., 2016; Sinclair et al., 2017). However, no studies isolate kicking spatiotemporal demands specifically and the impact on collecting players, therefore no conclusion can be drawn on the spatiotemporal requirements of kick types and their related outcomes.

Therefore, the aim of the current chapter was to assess the spatiotemporal characteristics of these kicks to inform the physical demands of a successful kick chase. This will be directed by the following research questions.

- What are the typical distances and collection times (and therefore required kick chase speeds) of different kick types and in different areas of the field?
- What are the spatiotemporal requirements of kick collection in different scenarios on the field, based on the outcome of both the kick itself and the actions of the collecting player?
- How can kicks be grouped by distance-time requirements?

## 7.3 Methods

This chapter utilised the same dataset used in Chapters 5 and 6, with further data manipulation completed as discussed in the following section. This includes the same definitions of kick types and zones given in the general methods (Table 3.4, Table 3.5 and Figure 3.3).

### 7.3.1 Variable Calculations

#### 7.3.1.1 Distance and Gain Calculation

The distance of kicks ($d$) was calculated using the Euclidean distance formula :

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}. \tag{2}$$

Where $x_1$ and $x_2$ were the start and end $x$ coordinates and $y_1$ and $y_2$ were the start and end $y$ coordinates. The gain of kicks ($g$) was identified by calculating the difference in the initial $x$ coordinate and end $x$ coordinate (i.e pitch length).

$$g = (x_2 - x_1). \tag{3}$$

Where $x_1$ and $x_2$ were the start and end $x$ coordinates.

#### 7.3.1.2 Collection Time

Collection time was deduced by finding the next adjacent collection to the kick and measuring the difference in the timestamp the kick was taken and the timestamp the collection was made. This utilised the rolling clock rather than the match time, to the closest 0.01 s, as this allows a greater degree of accuracy in the difference, and the rolling clock would not stop in between these actions. A collection was not coded for 1961 kicks, due to these kicks going into touch, or the whistle being blown for a kicking error or previous penalty before a collection could be coded. These kicks were removed from analysis.

#### 7.3.1.3 Speed and Gain Speed Calculation

Average speed was calculated using the kick distance and collection time, using the following formula:

$$s_{distance} = \frac{d}{t}, \tag{4}$$

Where $s_{distance}$ denotes the average speed, $d$, the distance and $t$ the time. There is yet to be a study quantifying the average speed of different kick types in rugby, so the following studies have been used as a base to create a filter of the average speed in this dataset. In such studies, the mean ball speed ranged from 25-27 $ms^{-1}$ with standard deviations between 2-5 $ms^{-1}$ (Ball et al., 2013; Sinclair et al., 2017). Given this, an upper limit of 40 $ms^{-1}$ was used as an approximate of the mean plus three standard deviations from these studies, to filter any abnormally high speeds. This is in line with Holmes et al. (2006), who reported kickers could reach a speed of 38.1 $ms^{-1}$ with a maximal effort kick of no particular style. A lower limit was not applied as none of these studies investigated low kicks, these kicks are likely to experience higher friction as they travel along the field, as they tend to make contact with the ground multiple times, hence this may lower the speed of the ball. Conversely, kicks such as bomb and box kicks may spend a long time in the air, lowering the speed of the ball again.

The gain speed was calculated using the kick gain and collection time as follows:

$$s_{gain} = \frac{g}{t}. \tag{5}$$

Where $s_{gain}$ denotes the average gain speed, $g$, the gain and $t$ the time. No gain speeds exceed the limit described above, hence no kicks were removed on that basis.

### 7.3.2 Data Removal

The same dataset from the previous chapter was utilised, with 6587 kicks initially included. However, the following number of kicks were removed for the named reasons:

- 1961 kicks were removed as the collection time could not be calculated, as no collection was coded, meaning the kick was kicked into touch or the whistle was blown before the ball was collected.

- 46 kicks were removed for having a speed calculated above the 40 $ms^{-1}$ threshold described above.
- 129 kicks were removed as their direct outcomes were either into touch, a kicking team error or unassigned.
- 8 kicks were removed due to having a calculated distance of 0.

A final group of 4443 kicks was utilised in the analysis.

### 7.3.3 Statistical Analysis

The Kruskal Wallis test was used to compare the medians of distance, speed, collection time and gain between different groups.. This included comparing kick types, zones, outcomes and the outcome grouping. A Bonferroni correction was applied to account for multiple testing. The Dunn test was used post hoc to analyse pairwise differences.

#### 7.3.3.1 K-Means Clustering

K-Means clustering analysis was implemented to create clusters of kicks based on their distance and collection time (MacQueen, 1967). K-Means clustering works by randomly selecting a data point as a centroid of an initial cluster, for each of the k clusters. Surrounding data points are then assigned to a cluster based on distance (in this chapter, the Euclidean distance was used), and then the centroids of the clusters are recalculated from all points within. These steps are iterated until convergence when the centroids no longer move significantly or when the maximum iterations have been reached. This process is completed for multiple values of k and the best is chosen using evaluation metrics.

In this chapter, both within sum of squares (WSS), the gap statistic and the silhouette plots were used to evaluate the number of clusters.

The former, also known as the elbow plot, is traditionally used to identify the optimal clusters by finding the ″elbow″ of the data on the plot. This is identified as the point of inflection where the WSS begins to decrease at a slower rate. The percentage change was also used to confirm this elbow point. The gap statistic plot illustrates the differences between observed in-cluster dispersion compared to the expected dispersion under a null reference distribution. The silhouette plot measures the similarity between an object and its own cluster, compared to other clusters in the analysis.

K-Means clustering and similar clustering methods have been previously used in both rugby union and league to understand playing patterns, and positional differences (Coughlan et al., 2019; Dalton-Barron et al., 2022; Ungureanu et al., 2019). The use of this unsupervised learning mechanism is beneficial in rugby and related sports as it provides a bias-free approach to analysis, unlike supervised learning where the groups are preassigned to the data.

## 7.4 Results

### 7.4.1 Collection Spatiotemporal Requirements

Figure 7.1 displays a 3D surface plot of distance and time and the respective density of kicks in every region of the *xy* plane. This figure identifies that the majority of kicks had distance values between 20 and 40 m. The collection time of the majority of kicks tended to sit between 2-8 s, with the highest peak at approximately 3.25 s, and a lower peak at approximately 6.19 s.

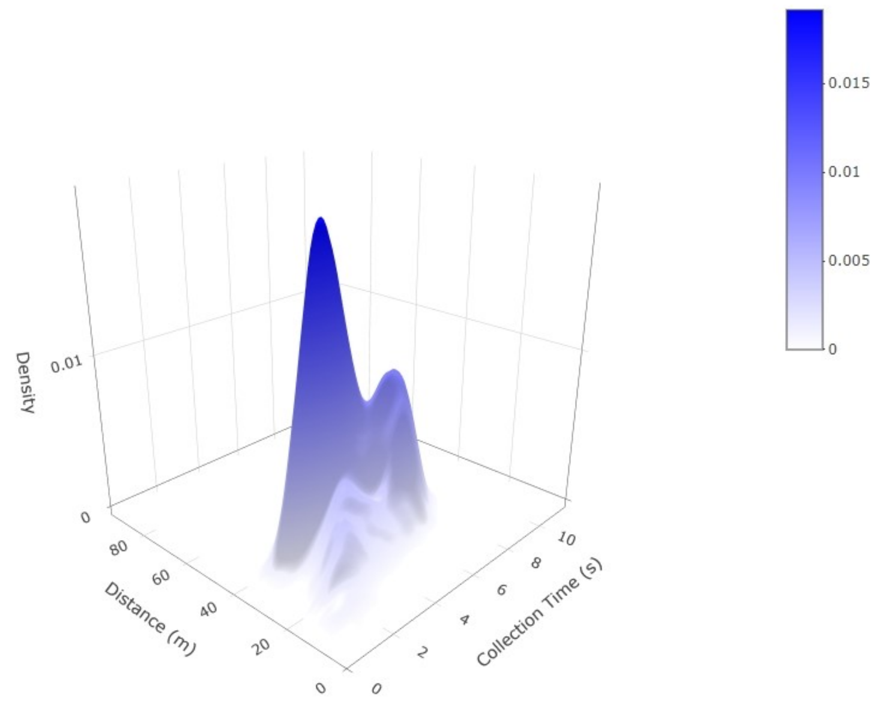



**Figure 7.1**
Distance-time surface plot. Distance (m) is represented by the $y$-axis, time (s) is represented by the $x$-axis and the $z$-axis displays the density of kicks at a given distance and time. The legend shows the scale of the density to aid interpretation.

Figure 7.2 illustrates the distance and time of kicks with the colour representing their kick zone. This figure demonstrates that the majority of kicks were taken from the blue (41%) and green (24%) zones (Appendix D.2). Most of these kicks tended to be over 35 m (52% and 73% respectively) and 3 s of collection time (88% and 90%) (Appendix D.2). Kicks in the gold zone tended to have lower distances with only 68% below 35 m and a range of collection times. Finally, this figure demonstrates that most red and some silver zone kicks were below 25 m (72% and 48%) with collection times of below 3 s (79% and 54%) (Appendix D.2).

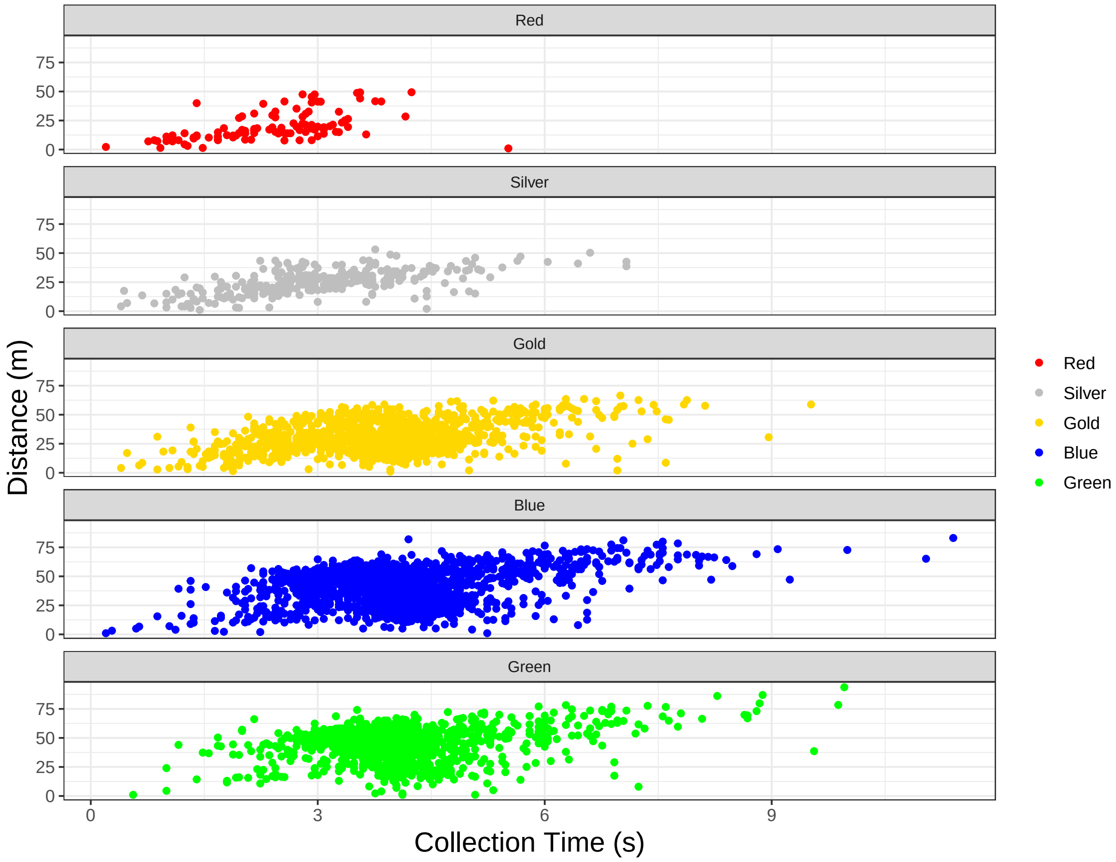



**Figure 7.2**
Distance-time scatter plot of kicks separated by zone. Distance (m) is represented by the $y$-axis, collection time (s) is represented by the $x$-axis with colour indicating kick zone. The plot has been faceted into zones.

There were differences between mean values of distance, collection time, speed and gain of kicks in different zones of the field based on the Kruskal Wallis test (Appendix D.2). Red zone kicks had the lowest mean distance and gain (19.8 $\pm$ 12.3, 11.3 $\pm$ 6.3 m, respectively), and recorded the shortest mean collection time (2.4 $\pm$ 0.9 s). Green zone kicks had the largest mean distance and gain, at 44.1 $\pm$ 14.8 m and 41.9 $\pm$ 15.6 m respectively. Table 7.1 illustrates the full breakdown of values, with mean distance and gain decreasing as a team moves along the field from a team's own try line to the opposition try line. Mean collection time also decreased with movement from a team's own try line to their opposition's try line. Finally, mean collection speed generally decreased as a team decreased their distance from the opposition try line, except in the gold zone, where kicks were collected quicker on average compared to the red and silver zones.

**Table 7.1**
Mean and standard deviation values of collection speed, distance and time by kick zone (Mean ± SD).

| Kick Zone | Kick Distance (m) | Collection Time (s) | Collection Speed ($ms^{-1}$) | Kick Gain (m) |
|---|---|---|---|---|
| Red | $19.8 \pm 12.3$ | $2.4 \pm 0.9$ | $8.3 \pm 4.1$ | $11.3 \pm 6.3$ |
| Silver | $24.9 \pm 10.5$ | $3.0 \pm 1.2$ | $8.7 \pm 3.8$ | $19.7 \pm 9.9$ |
| Gold | $30.2 \pm 12.5$ | $3.9 \pm 1.2$ | $8.2 \pm 3.8$ | $26.6 \pm 12.0$ |
| Blue | $37.6 \pm 15.6$ | $4.2 \pm 1.1$ | $9.5 \pm 4.3$ | $35.0 \pm 15.3$ |
| Green | $44.1 \pm 14.8$ | $4.1 \pm 1.1$ | $11.2 \pm 4.4$ | $41.9 \pm 15.6$ |

Figure 7.3 illustrates the distance of the kicks in metres, compared to the collection time in seconds of all kicks in the dataset. This figure separates the kicks into three clear groups by kick type, similar to the density peaks discussed in Figure 7.1. The first group included the territorial and touch kicks, indicated by the purple and pink dots. This group was outlined by a higher distance than other kick types with the majority over 35 m (83% and 100% respectively) and an extensive range of collection times (Appendix D.2). The touch kicks in this section were kicks that failed to make touch and were recovered by a player before going out of play.

The second clear group was the bomb and box kicks, indicated by red and orange respectively. This group depicted a shorter distance range between 15-35 m, with 81% and 72% in this range for bomb and box kicks respectively (Appendix D.2). Collection time ranged between 3-5 s in this group, again with 86% and 88% in this range for each kick type (Appendix D.2).

The third group was identified by the light green, dark green and blue dots, highlighting the chip, cross pitch and low kicks respectively. These kicks were categorised as low collection time, with the majority collected in less than 3 s (60%, 76%, and 57% respectively, Appendix D.2). Chip and low kicks tended to be kicked below 25 m (61% and 58%), whereas cross pitch tended to be higher distance kick, with only 8% kicked less than 25 m (Appendix D.2).

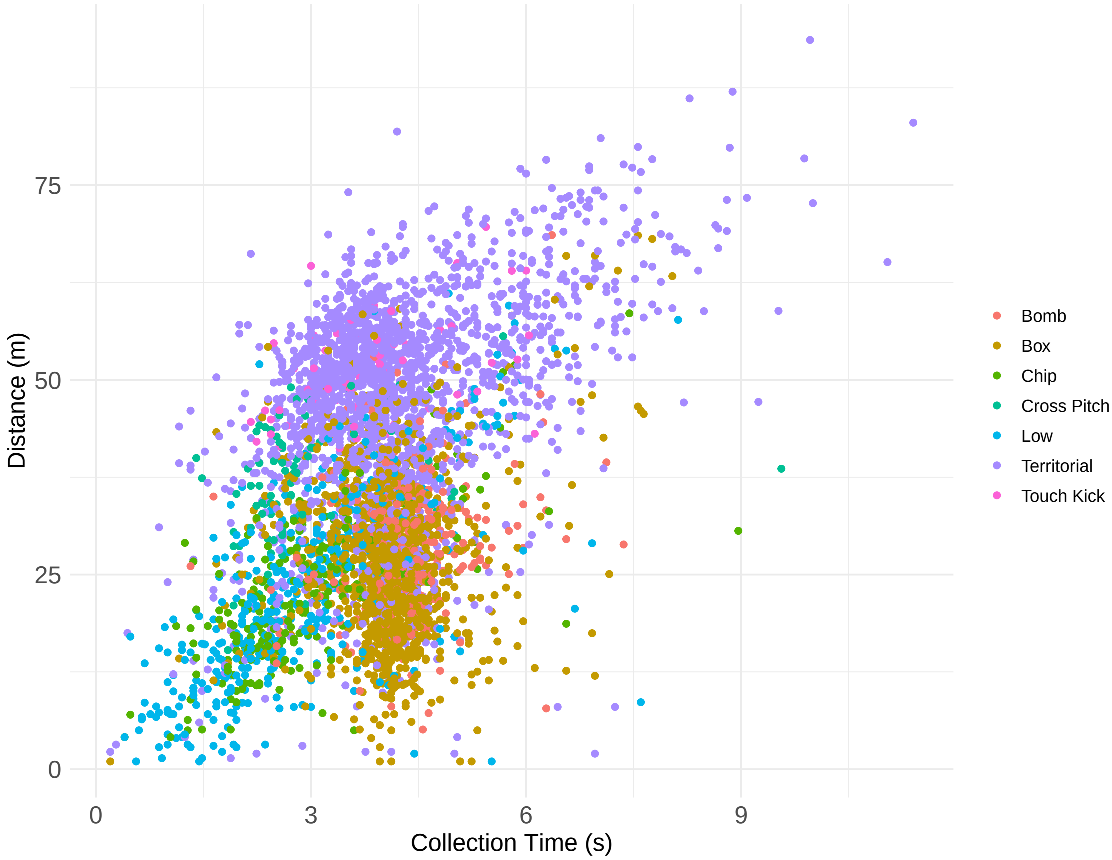



**Figure 7.3**
Distance-time scatter plot of kicks separated by kick type. Distance (m) is represented by the $y$-axis and collection time (s) is represented by the $x$-axis with colour indicating kick type.

Distance, speed, collection time and gain were also found to be significantly different between kick types based on the Kruskal Wallis test (Appendix D.3).

In Table 7.2, the mean and standard deviation for kick distance, collection time, speed and kick gain are given for each of the kick types. The range of mean distance was between 22.8 m to 51.4 m, whereas the gain range was 12.3 m to 46.9 m. The table demonstrated a clear divide in kick distance, between shorter kicks such as the bomb, box, chip and low kicks (ranging between 22.8 $\pm$ 12.1-28.3 $\pm$ 8.1 m), and longer kicks such as the territorial and touch kicks (47.2 $\pm$ 13.1, 51.4 $\pm$ 6.4 m respectively). Whilst in most kick types the distance and gain do not differ greatly, the cross pitch is different. The cross-pitch mean gain was lower than the mean distance of 12.3 $\pm$ 8.0 m, compared to a distance of 36.5 $\pm$ 7.6 m.

The range of mean collection times was from 2.9 to 4.4 s. Analysing collection times, chip, cross pitch and low kicks were associated with lower mean collection times (M = 2.9 ± 1.2, 2.9 ± 1.1 and 2.9 ± 1.3 s respectively), and bomb, box, territorial and touch kicks with higher mean collection times (4.4 ± 0.7, 4.1 ± 0.7, 4.2 ± 1.3 and 3.8 ± 1.0 s).

Mean collection speeds ranged from 6.6 $ms^{-1}$ to a top mean speed of 14.2 $ms^{-1}$. Touch, cross pitch and territorial kicks had higher recorded speeds of 14.2 ± 3.3, 13.5 ± 3.8 and 11.9 ± 4.1 $ms^{-1}$ respectively. Chip and low kicks had slower collection speeds, both at 8.0 ± 2.8 $ms^{-1}$ and 8.0 ± 3.5 $ms^{-1}$. Finally, the bomb and box kicks had the slowest mean collection speeds, with 6.6 ± 2.2 and 6.7 ± 2.8 $ms^{-1}$ respectively.

**Table 7.2**
Mean and standard deviation values of collection speed, distance and time by kick type (Mean ± SD).

| Kick Zone | Kick Distance (m) | Collection Time (s) | Collection Speed ($ms^{-1}$) | Kick Gain (m) |
|---|---|---|---|---|
| Bomb | 28.3 ± 8.1 | 4.4 ± 0.7 | 6.6 ± 2.2 | 24.3 ± 8.4 |
| Box | 26.9 ± 9.8 | 4.1 ± 0.7 | 6.7 ± 2.8 | 25.4 ± 9.6 |
| Chip | 22.8 ± 9.3 | 2.9 ± 1.2 | 8.0 ± 2.8 | 20.4 ± 9.0 |
| Cross Pitch | 36.5 ± 7.6 | 2.9 ± 1.1 | 13.5 ± 3.8 | 12.3 ± 8.0 |
| Low | 22.8 ± 12.1 | 2.9 ± 1.3 | 8.1 ± 3.5 | 19.9 ± 12.8 |
| Territorial | 47.2 ± 13.1 | 4.2 ± 1.3 | 11.9 ± 4.1 | 44.1 ± 13.7 |
| Touch Kick | 51.4 ± 6.4 | 3.8 ± 1.0 | 14.2 ± 3.3 | 46.9 ±9.9 |

### 7.4.2 Collection Demands within different situations

Figure 7.4 displays the same distance-time scatter plot but now with colour used to indicate the outcomes of the kicks. This figure did not illustrate clear groups as the previous distance-time scatter plot. The red dots indicated the opposition had caught full, signifying the ball was collected before it touched the ground (Caught Full). This group had a range of distances but the collection time was between 3-5 s, with 85% collected within this range (Appendix D.2). The orange represents kicks collected on the bounce (Collected Bounce), this covered a range of distances and times, illustrating that both short and long kicks are caught by the opposition on the bounce.

After 5 s, the vast majority of kicks in this area of the figure were collected on the bounce, suggesting that 5 s was likely the upper flight time of kicks within this dataset. Linking back to Figure 7.3, it suggests that the territorial and touch kick group identified previously was almost always collected by the opposition (Figure 7.3). However, the bomb and box group was split between opposition and kicking team collection, with similar collection time ranges (Figure 7.3).

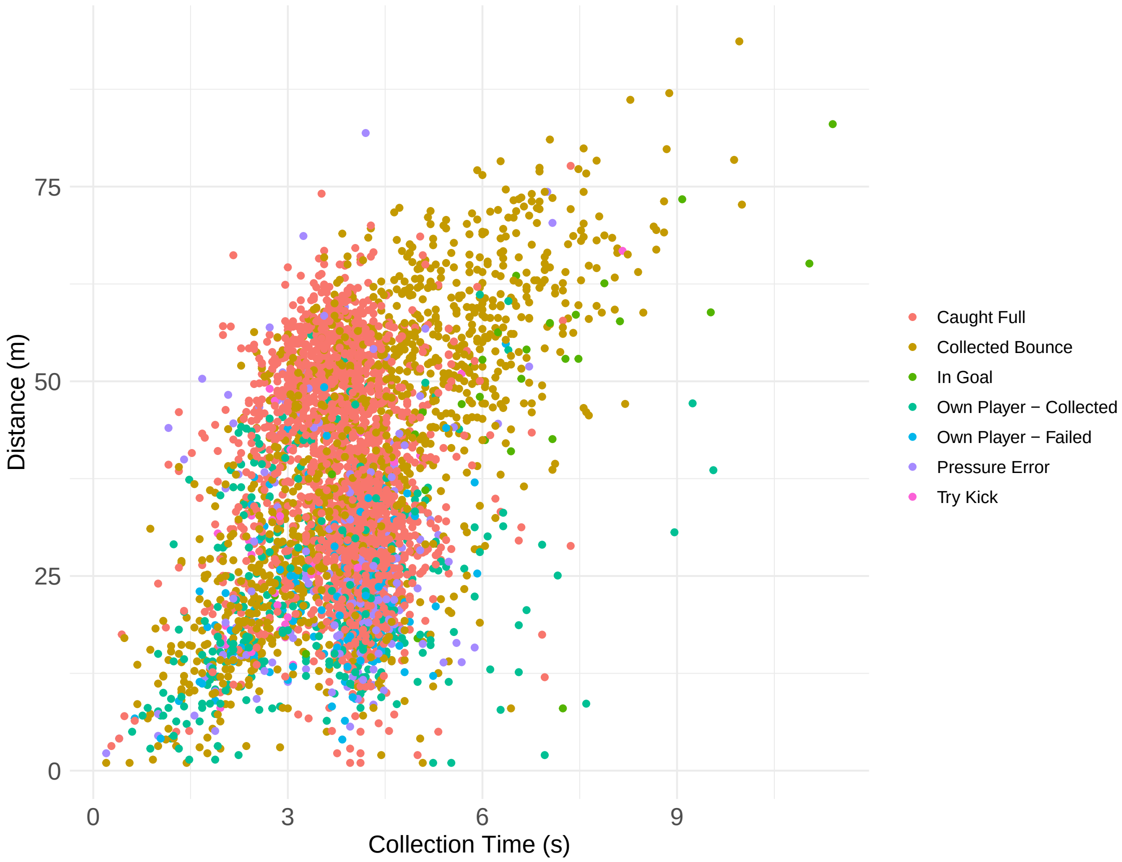



**Figure 7.4**
Distance-time scatter plot of kicks separated by kick outcome. Distance (m) is represented by the $y$-axis and collection time (s) is represented by the $x$-axis with colour indicating kick outcome.

In Figure 7.5, one key group is the green points representing Group 3 (kicks that were kicked by the collecting player before being tackled), which map similarly to the territorial kicks, equally 81% of these kicks had a distance over 35 m similar (Appendix D.2) to the territorial kicks seen in the previous figure (Figure 7.3). A large density of the Group 1 points map across the 3 to 5 s collection time group (74%, Appendix D.2), similar to where box and bomb kicks have been observed in the previous figure (Figure 7.3).

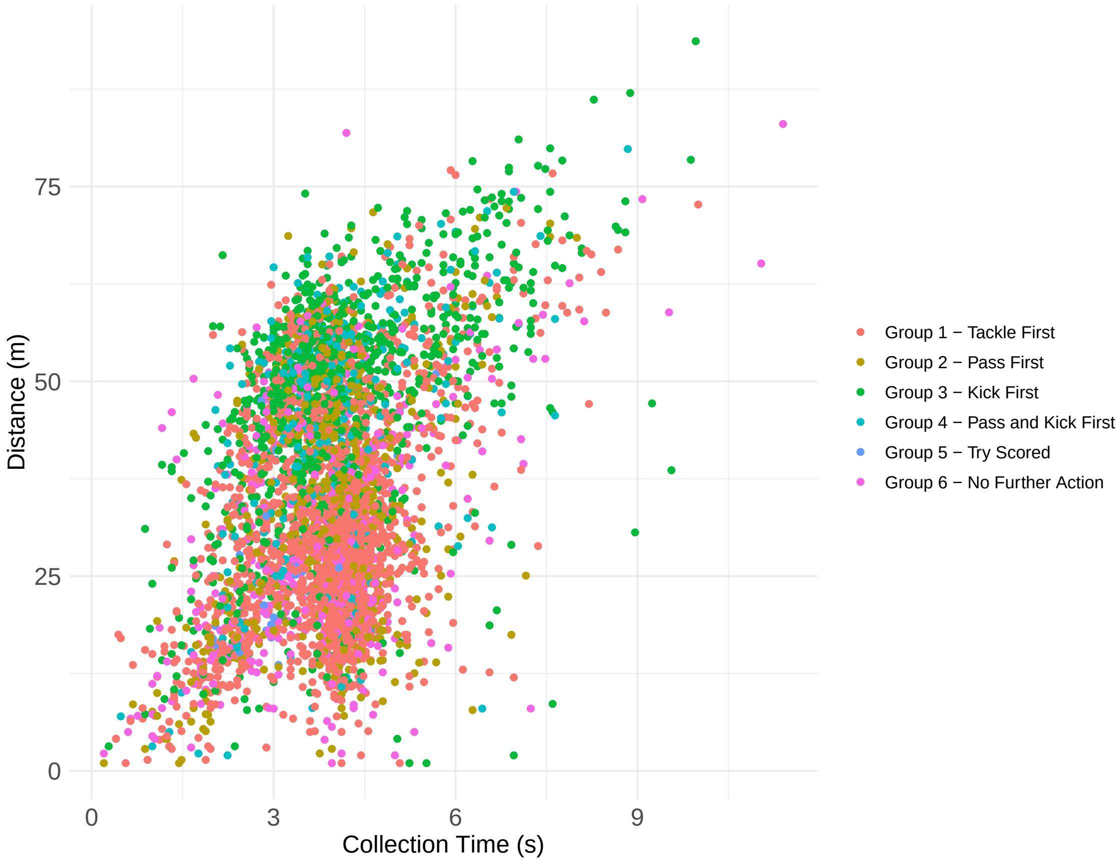



**Figure 7.5**
Distance-time scatter plot of kicks separated by kicks next action. Distance (m) is represented by the $y$-axis and collection time (s) is represented by the $x$-axis with colour indicating the action that took place after the kick was collected.

Examining the distance and gain from the perspective of the kick outcomes also demonstrated differences between the groups. The range of mean distances when split by outcome was between 22.6 to 44.6 m, whereas the gain was 15.7 to 42.7 m. Lower mean distances are observed in outcomes such as Own Player Collected or Failed, Pressure Error, and Try Kick (22.8 ± 11., 23.3 ± 9.1, 26.7 ± 12.3, 28.6 ± 13.0 m). Longer mean distances were observed where the opposition caught the ball on the full or the bounce (Caught Full and Collected Bounce) (37.6 ± 13.1, 40.8 ± 17.8 m), and when the ball was touched by the opposition in the in-goal area (In Goal) (M = 44.6 ± 17.8 m). A similar set of differences was observed in the mean gain values per group and can be viewed in Table 7.3.

The difference in collection time was minimal between the outcomes, except the In Goal group in which the mean collection time was 6.2 ± 2.1 s, while the rest of the outcomes demonstrated values between 3 and 4 s.

The mean collection speeds divided the outcomes into two groups, with Caught Full, Collected Bounce and Try Kick recording higher collection speeds (M = 10.2 ± 4.5,9.8 ± 3.7 and 9.1 ± 3.4 $ms^{-1}$ respectively) and the rest of the outcomes associated with lower mean collection speeds, ranging between 6.5 and 7.4 $ms^{-1}$.

Distance, speed, collection time and gain were also significantly different between kick outcomes based on the Kruskal Wallis test. A full breakdown of the hypothesis testing can be found in Appendix D.3.

**Table 7.3**
Mean and standard deviation values of collection speed, distance and time by kick outcome (Mean ± SD).

| Kick Zone | Kick Distance (m) | Collection Time (s) | Collection Speed ($ms^{-1}$) | Kick Gain (m) |
|---|---|---|---|---|
| Caught Full | 37.6 ± 13.1 | 3.9 ± 0.7 | 10.2 ± 4.5 | 35.4 ± 13.1 |
| Collected Bounce | 40.8 ± 17.8 | 4.3 ± 1.6 | 9.8 ± 3.7 | 37.9 ± 17.6 |
| In Goal | 44.6 ± 17.5 | 6.2 ± 2.1 | 7.3 ± 1.8 | 42.7 ± 18.3 |
| Own Player - Collected | 22.8 ± 11.1 | 3.6 ± 1.4 | 7.0 ± 4.0 | 15.9 ± 9.9 |
| Own Player - Failed | 23.3 ± 9.1 | 3.8 ± 0.9 | 6.5 ± 2.7 | 19.1 ± 7.7 |
| Pressure Error | 26.7 ± 12.3 | 3.9 ± 1.0 | 7.4 ± 4.6 | 23.3 ± 12.2 |
| Try Kick | 28.6 ± 13.0 | 3.2 ± 1.2 | 9.1 ± 3.4 | 19.6 ± 12.2 |

From Table 7.4, mean kick distances ranged from 30.2 to 47.1 m with mean gain ranging from 20.6 to 44.2 m. The range of mean collection times was between 3.3 to 4.1 s, whilst mean collection speeds were between 8.2 to 12.1 $ms^{-1}$. Groups 2 and 3, kicks where the collecting player had time to make a kick, or both a pass to another teammate who could then kick, had the highest mean distance and gain (47.1 ± 14.6 and 43.5 ± 14.6 m and 44.2 ± 15.2 and 43.5 ± 14.6 m respectively for each outcome), as well as higher mean collection speeds (12.1 ± 4.1 and 11.2 ± 4.0 s). Group 5, where the collecting player scored a try, had the lowest mean distance and gain (28.5 ± 11.3 and 20.6 ± 10.5 m), and mean collection time (3.3 ± 0.9 s). Other than Group 5, the mean collection time did not deviate largely between groups.

Distance, speed, collection time and gain were significantly different between kick groups, based on the Kruskal Wallis test. A full breakdown of the hypothesis testing can be found in Appendix D.3.

**Table 7.4**
Mean and standard deviation values of collection speed, distance and time by group based on next action after the kick was collected (Mean ± SD).

| Kick Zone | Kick Distance (m) | Collection Time (s) | Collection Speed ($ms^{-1}$) | Kick Gain (m) |
|---|---|---|---|---|
| 1 - Tackle First | 30.9 ± 13.3 | 3.9 ± 1.0 | 8.2 ± 3.8 | 27.8 ± 13.3 |
| 2 - Pass First | 35.2 ± 15.0 | 3.9 ± 1.0 | 9.3 ± 4.0 | 32.5 ± 15.0 |
| 3 - Kick First | 47.1 ± 14.6 | 4.1 ± 1.4 | 12.1 ± 4.1 | 44.2 ± 15.2 |
| 4 - Pass and Kick First | 43.5 ± 14.6 | 4.0 ± 1.1 | 11.3 ± 4.0 | 41.0 ± 14.9 |
| 5 - Try Scored | 28.5 ± 11.3 | 3.3 ± 0.9 | 8.8 ± 2.7 | 20.6 ± 10.5 |
| 6 - No Further Action | 30.2 ± 14.1 | 3.8 ± 1.4 | 8.6 ± 4.5 | 26.0 ± 14.5 |

### 7.4.3 Clustering Analysis

A K-Means cluster analysis was run on the dataset. The number of $k$ clusters was optimised using an elbow plot containing the total WSS, with the ″elbow″ observed at $k$ equal to four, indicating that four was the optimum number of clusters for this dataset. This was confirmed by checking the largest difference in percentage change between the WSS values. The elbow plot can be viewed in Figure 7.6.

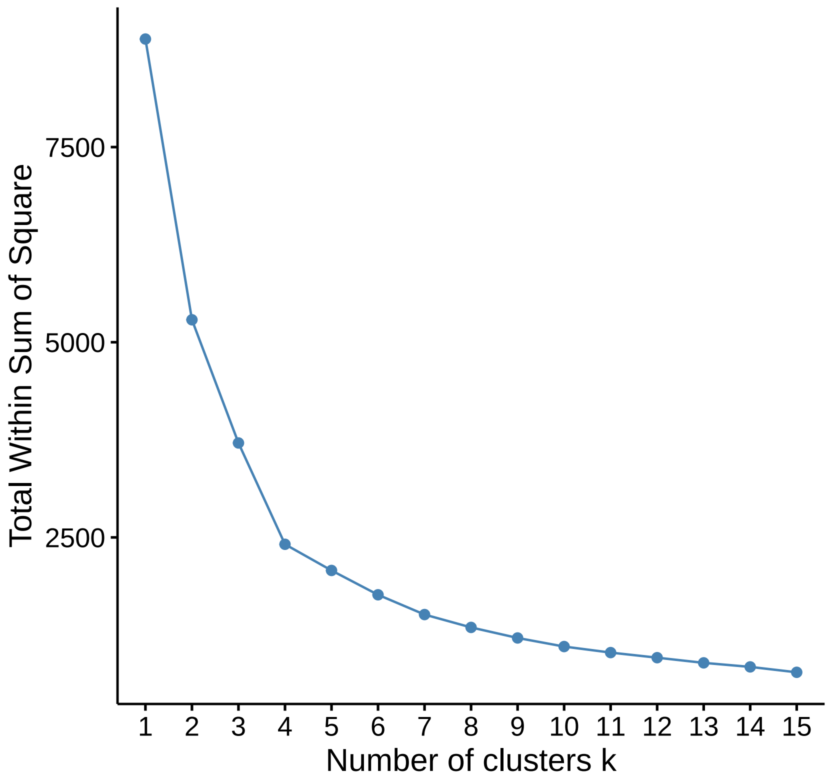
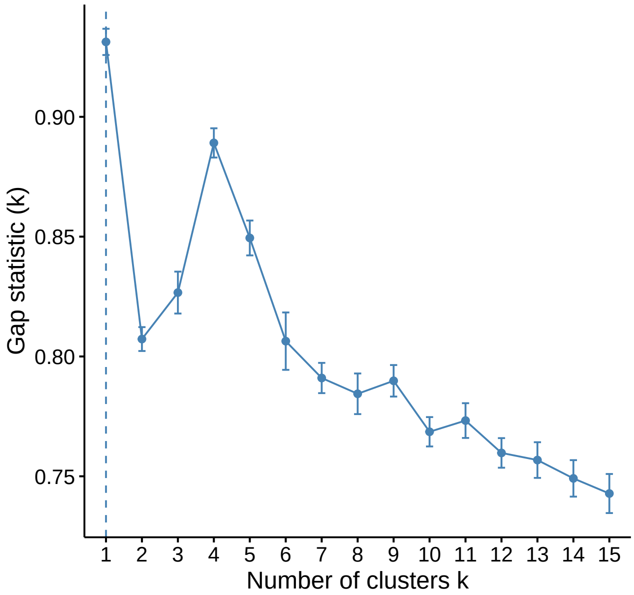
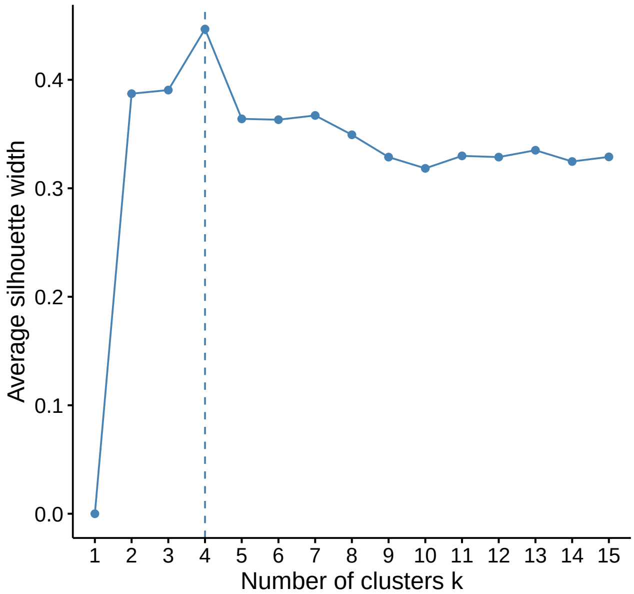



**Figure 7.6**
Elbow plot illustrating the total within sum of squares (WSS) as a function of the number of clusters ($k$) for the dataset. The plot displays a characteristic 'elbow' pattern, indicating the optimal number of clusters. The elbow point represents the point of diminishing returns in terms of WSS reduction, in this case, this value is at 4.

The gap statistic plot (Figure 7.7a) suggests similar, despite the $k = 1$ cluster having the highest gap statistic, the second highest value sits at $k = 4$. Using $k = 1$, would not separate the kicks into any clusters, therefore based on this, and the previous plot, $k = 4$ was chosen. The silhouette plot also confirmed $k = 4$ as the optimal cluster number (Figure 7.7b).




**(a)**




**(b)**

**Figure 7.7**
Gap statistic plot displaying the optimal number of clusters for the given dataset. The $y$-axis represents the gap statistic, and the $x$-axis represents the number of clusters ($k$). Silhouette plot illustrating the quality of clustering for various numbers of clusters. The $y$-axis shows the average silhouette score, and the $x$-axis represents the number of clusters ($k$). Higher silhouette scores indicate better-defined clusters, with the optimal number of clusters identified by the highest average silhouette score. Plots suggest an optimal $k$ value of 4.

This creates four distinct clusters, represented in Figure 7.8. Cluster 1, identified by the red squares, can be observed in the bottom left of this diagram, the cluster centre is at a collection time of 2.29 s and a distance of 21.0 m (-1.42 and -0.96 when scaled for analysis). The blue circles signify the second cluster of this analysis, centred at 4.23 s and 25.8 m (0.22, -0.66 scaled values). The third cluster, categorised by green triangles, has a centre at 6.19 s and 57.5 m (1.88, 1.38) and the final cluster, identified by grey crosses, has a centre at 3.70 s and 48.9 m (-0.22, 0.83).

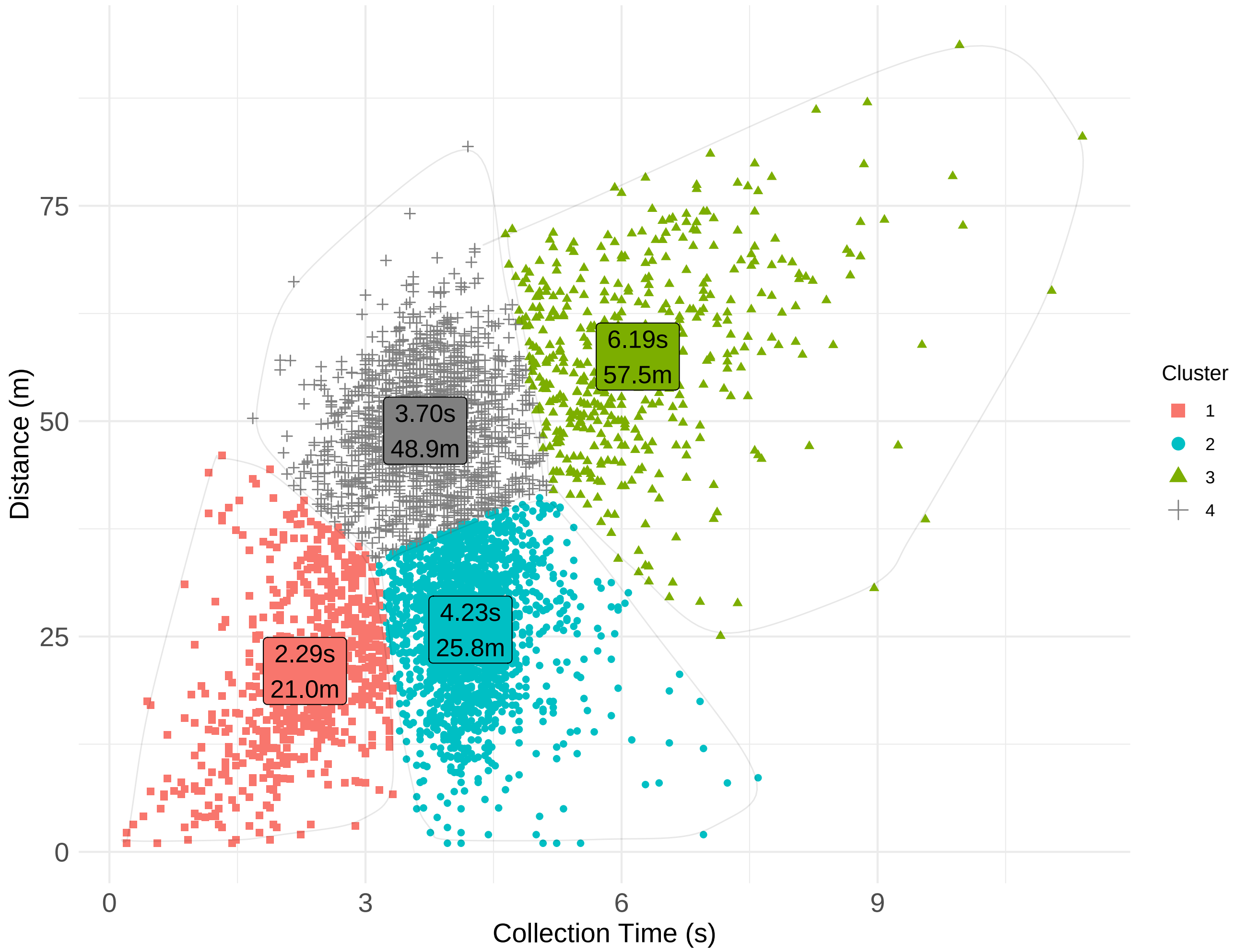



**Figure 7.8**
Cluster diagram illustrating the results of K-Means clustering analysis, based on scaled distance-time measurement of the kicks in the dataset. Each data point is represented by a coloured marker corresponding to its assigned cluster. The plot provides a visual representation of the distinct clusters and their spatial distribution in the feature space. The analysis identified four clusters (Cluster 1, Cluster 2, Cluster 3 and Cluster 4), each exhibiting unique characteristics and spatial arrangement. Labels indicate each cluster's mean distance (m) and time (s).

## 7.5 Discussion

The primary aim of this chapter was to assess spatiotemporal characteristics of kicks to inform the physical demands of a successful kick chase, this was analysed by calculating speed, distance and collection time values across different kick types, and in different circumstances, as well as investigating whether these values can be used to group kicks into a streamlined set of kicks. From the current chapter results, it has been demonstrated that different kick types have significantly different spatiotemporal profiles (Figure 7.3, Table D16), with the clearest similarities between i) territorial and touch kicks, ii) bomb and box kicks, and iii) attacking kicks (chip, cross pitch and low). Comparing kick outcomes, there was a contrast in mean collection distance (Table D21), with kicking team collection attempts, pressure errors and try kicks associated with lower kick distance. Furthermore, when kicks are grouped by the next actions that take place, there are clear distinctions (Table D26), particularly observed when players who caught kicks had time to make a pass or another kick. Clustering analysis also revealed that all kicks can be grouped into four main clusters based on distance and collection time.

### 7.5.1 Collection Demands

Distance, collection time, speed and territorial gain were identified as significantly different between different kick zones. Analysing the spatiotemporal metrics, with the context of the kick zone identifies changes across the field of play. It is clear, firstly, as observed in the previous chapter, that green and blue zone kicks form a majority of the kicks taken in this dataset. These kicks range in collection distances and times but generally have higher collection speeds. Overall, the zone categories suggested that kick distance and gain decrease as a team moves along the field towards their opposition's try line. Equally, the collection speeds appeared to also decrease as a team moves down the field, as does the collection time. This illustrates a shortening of kicks over the field, suggesting that tactics within a team's own half are naturally more territorial-based strategies with longer distanced kicks and longer collection times, whilst into the opposition half, teams lean more towards attacking-based strategies, with short distances and collection times. These results suggest that the change point between territorial and attacking strategies may be in the natural position of the centre of the field. This suggests that kicking may become more time-critical as a team ascends towards their opposition's try line, with stricter response times required from supporting players.

When analysing the collection demands, namely distance, collection time, speed and gain, it was demonstrated that there were significant differences between different kick types. This section of analysis identified three groups of kick types, based on their distance-time values. The first group was the territorial and touch kicks, identified by both longer distances, mostly beyond 40 m, and a large range of collection times. Furthermore, the similarity between the mean distance and gain time also suggests these kicks are not generally angled across the field from the kicker. It was also observed that they have the highest mean distance compared to the other kicks, despite having a similar range of collection times. This suggests that these kicks are often collected quickly, mostly from the opposing team as the previous chapter had suggested. This has applications potentially for team selection, using this information, teams may choose to select a kick chaser who is capable of reaching a similar speed to the collection speed to provide the first defensive pressure on the ball carrier (Kraak et al., 2016). This highlights that territorial kicks tend to follow their definition given their high mean distance and gain. Territory has been previously identified as a part of a successful part of winning identity in test rugby (M. T. Hughes et al., 2012), hence, it may be that the ability to support territorial kicks influences success. Lazarczuk et al. (2020) had previously reported that the fly half and full back positions tend to perform these kicks proportionally more than other backline players, suggesting a positional alignment with this group of kicks.

Bomb and box kicks form the second group. This group was associated with a range of distances but mean values of 4.1-4.4 s, suggesting that the longer of these kicks may be slower and ″hang″ in the air. The mean distance for these kicks was much lower than the previous group (26.8-28.3 m), suggesting that they may be more practically collected by the kicking team themselves. These have a similar mean gain and distance, suggesting they are generally kicked straight from the kicker rather than angled across the field. These kicks appear to give the ball time in the air, which may give kicking team players more time to position themselves correctly to contest the ball compared to attacking-style kicks. Territorial advantage appears to still be given from these kicks, compared to the opposing team based on the mean gain. It may be that teams can use these kicks for both the aim of collecting themselves or the aim of kicking to the opposition and putting pressure on them. With box kicks predominantly performed by scrum halves (Lazarczuk et al., 2020), these results may be more relevant for teams who predominantly kick through their scrum half.

The third group was the attacking style kicks, including chip, cross pitch and low kicks. There was a small divide between the chip and low kicks and cross-pitch kicks. Chip and low kicks tended to have shorter distances in this group whilst cross-pitch had longer distances. All kick types maintained a shorter collection time than the territorial and box kick groups discussed in the previous paragraphs. These are a ″quick″ style of kick given their distance-time profiles, signifying players need to be able to react quickly to regain possession. Chip and low kicks mean gain values were similar to their distance, suggesting they are not angled far from the direction of play. However, cross-pitch kicks had a larger difference between the mean gain and distance, over 20 m. This is likely caused by the angle used by the kicker to kick across the pitch, as their name suggests. Understanding the distances, speeds and times from these kicks will directly help build drills to prepare for regaining these kicks in the game. For example, chip and low kicks had a mean collection time of 3 s - in a drill, a kicker could take a kick and aim to collect in this time frame with the further extension including a second nearby player who may collect the kick instead. However, in drills practising cross-pitch techniques, it is more important that a supporting player can reach the kick across the field. This will require practice to coordinate in the short three-second window, as well as ensure players can reach the $12.3 \pm 8$ m gain as they will need to be onside from the kick (Table 7.2). Equally, teams could consider adding 10, 20, 30 metre sprint tests into their testing battery to understand the current skills of athletes they have on their roster, and how it links to these kick distances, collection times, and speeds.

### 7.5.2 Collection demands within different situations

It was identified that there were differences in distance, speed, collection time and gain between different kick outcomes and outcome groupings within this chapter. When collection demands were analysed in the context of the different outcomes both for the kick itself and the receiving player, the patterns were less obvious than observed in the previous section but still demonstrated some groupings. Firstly, by analysing the kick outcome directly, there was a clear group of kicks Caught Full from a range of distances as well as a range of collection times for the kick collected on the bounce (Collected Bounce). Linking with the previous results on kick types, these two outcomes split the territorial kicks into two groups, those caught fully identified by shorter collection times, and those collected on the bounce with longer collection times. However, given the wide range of times and distances on kicks collected on the bounce, that suggests that both short and long kicks are collected in this manner. This result also suggests that the end point of flight time of a rugby ball may be around 5 s based on the outcomes observed in this dataset, with kicks collected after this time likely collected from a bounce or the ground.

Areas where the bomb and box kicks were common in Figure 7.3, appear to map to both being collected successfully and unsuccessfully by the opposition, and successfully and unsuccessfully collected by the kicking team - highlighting that these kicks may be ″contested″ by both teams in a match. Given these kicks traditionally are shorter distances, but with a longer collection time, it suggests there is an opportunity for both teams to reach the ball. Moreover, if both teams are reaching the end point of the kick at a similar time, it may be that the contest is driven less by the speed of players and more by their position or aerial ability. This requires further analysis to underpin the key features of a successfully contested box or bomb kick.

On the contrary, with some consideration given to outliers, the kicks that were attempted to be collected by the kicking team tend to have faster collection times and lower distances. There were similar observations for Try Kick and Pressure Error outcomes, both of which encompass the kicking team making a reasonable effort to reach the ball after it has been kicked. This idea of ″contestability″ is consistent when the mean values for distance are calculated for these outcomes, with the Own Team collection outcomes, as well as the Try Kick and Pressure Error outcomes reporting lower mean distances and gain values, compared to higher values observed in Caught Full and Collected on the Bounce outcomes. Another result from these calculations was the relationship between the distance and gain in the outcomes. Considering kicks successfully collected by the kicking team and kicks that led to tries for the kicking team, the mean distance and gain tended to differ more than outcomes where the kick is unsuccessfully contested, with gain at around 70% of distance compared to 80% in the latter. As the difference between distance and gain increases, this suggests that the kick is more angled across the field and angled kicks may be more suitable to be collected by individuals other than the kicker. Overall, there may be a suggestion here that angling kicks may make them more likely to be collected successfully; however, future analysis of this is required to understand if this is the case in practice.

Based on the current analysis of the actions of the collecting player, it is clear that, across a large number of scenarios, the collecting player is tackled before a pass or kick is made. After approximately 40 m, the collecting player will have more options to take further action before being tackled. The kicks where either a kick or a pass and a kick were made by the collecting player have large overlaps to the position where the territorial kicks were observed in the previous section, suggesting this line of action is more common when these kicks are made. This supports ″kicking battles″, which have been discussed previously. These are situations where teams have time to recover kicks and return them to the opposition. These battles have been noted as areas of interest in this thesis and are a hypothesised area of benefit for teams. This analysis supports them being a part of the game, but further research is needed, likely in the form of video analysis, to understand their benefit.

Furthermore, similar to the kick outcomes previously analysed, the mean distances from these groups tended to group into ″contestable″ and ″uncontestable″ kicks. Situations where the player has time to make an additional kick or a pass to another player to kick, tend to have a higher mean distance and gain than those where the player is tackled before they can pass or kick the ball. Equally, the mean distance of kicks in situations where a collecting player has time to pass was in between these mean values, possibly the edge of where a kick can be contested by a kicking team, by either putting pressure on the collecting player or attempting to collect themselves. The try scored group (Group 6) had a lower mean distance, very similar to the same outcomes observed in the Try Kick outcome. This circumstance is likely a difficult read for the defender, who has to choose between attempting to collect the ball themselves or defending against the collecting player. This links to Chapter 6 results, where it was reported that winning teams had higher proportions of tries scored and lower rate of tries conceded in kicking sequences. This may be a skill more prominent in winning teams who may benefit both attacking and defending within this circumstance. The mean gain differs from the mean distance, at around 70% of the mean distance, which suggests this tactic employs angled kicks, which may be collected by teammates adjacent to the kicker.

### 7.5.3 Cluster Analysis

The clustering analysis of this data brings an independent view of how these kicks relate to each other in terms of distance and time. This analysis split the kicks into four groups, which can be related to the context of the game. The clustering does not bias towards their kick type, outcome or following action; this analysis simply categorised all kicks by distance-time.

The first cluster grouped short distance kicks that had short collection times. These may be categorised as ″fast″ contestables where most kicks are attacking-style kicks and are often collected by the kicking team. This cluster maps well both to attacking style kicks including chip, cross pitch and low (69% of kicks in this cluster belonged to one of these kick types) as well as kicks taken in the red and silver zone (36% of kicks in cluster from these zones). From this cluster, 31% were collected by the kicking team, of which 4% led to a try. This correlated with the importance of red zone kicking reported in Chapter 6, suggesting that the use of shorter, contestable kicks may be linked to sequence success, especially in winning teams. Other literature has reported that kicking in this ″dangerous″ area of the field may allow teams to form attacks closer to their opposition try line (Stanhope & Hughes, 1997).

The second cluster identified kicks with a short distance but longer collection time, mapping well with the box and bomb kick types previously observed (73% of kicks in this cluster). These kicks may be considered ″slow″ contestables, given the mixture of outcomes observed in this cluster with the shorter distance allowing contest of ball possession (Nakagawa, 2006). In this cluster, the collecting player was tackled before any further action 63% of situations, suggesting a pressure on the collecting player.

The third cluster had a different profile with both longer distance and collection time values. This maps around some of the territorial kicks (82% of kicks in this cluster were territorial), but does not cover this whole group. However, when the outcome and kick types are taken into consideration, there are some links. This cluster tends to centre around territorial kicks caught on the bounce (82% of outcomes of this cluster kicks), suggesting this group may represent kicks not well collected by the opposition. This group could be identified as ″slow″

territorials, where the opposition takes time to collect the ball. This kick style may be driven by teams ″testing″ out their opposition in the hope of forcing an error (Kraak et al., 2016). This cluster is likely to include kicks that feature in the previously mentioned ″kicking battles″, given 55% of these kicks belonged to Groups 3 and 4, indicating the collecting player either kicked or passed to a teammate who returned the kick.

Finally, the fourth cluster is composed of a longer distance kick with faster collection times. This group maps well to a section of territorial kicks (again 80% of the kicks in this cluster), specifically those that tend to be caught full rather than after a bounce (69% of outcomes). This group could be described as the ″fast″ territorials, a group where kicks are long distanced but collected quickly. Teams may use these styles of kick to put pressure on their opposition by aiming to tackle the collecting player rather than contest the ball itself, which may lead to error from the opposition (Kraak et al., 2016). However, it is likely these kicks also form part of ″kicking battles″ with 51% leading to a kick or pass and kick from the collecting player.

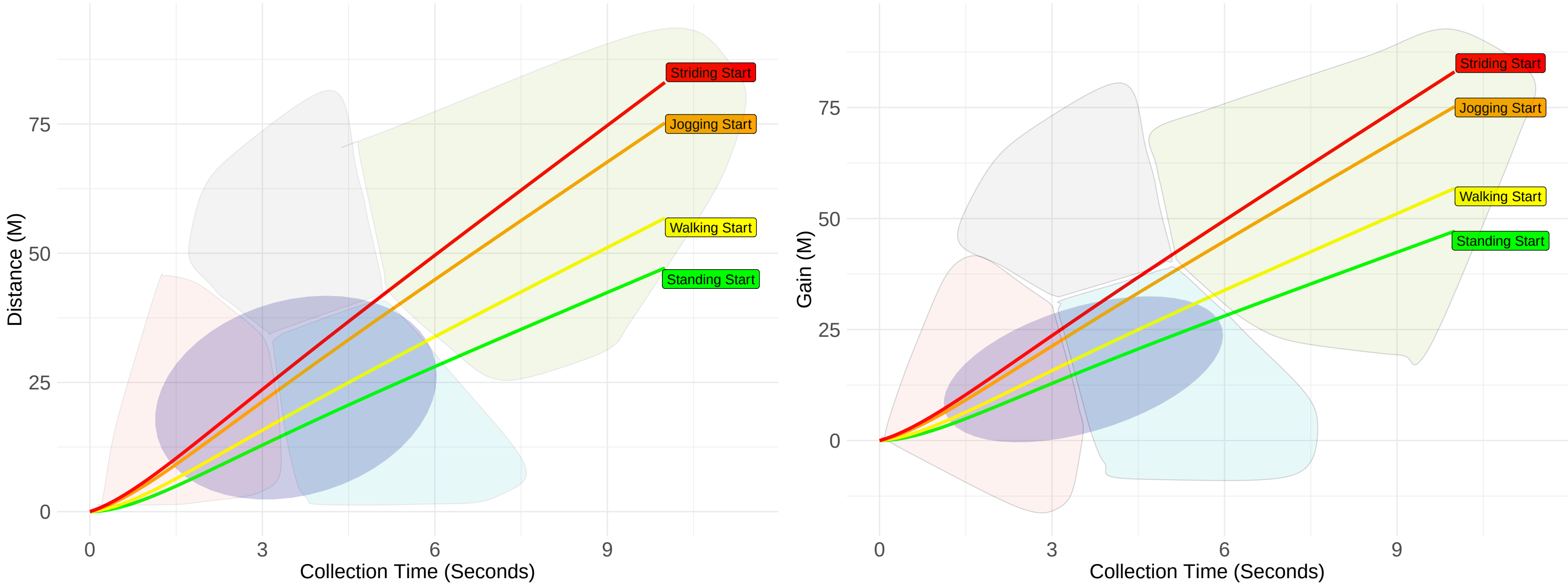
The ability to split kicks into these four groups of ″slow″ and ″fast″ contestable and ″slow″ and ″fast″ territorial kicks may benefit practitioners in terms of simplified messaging. Teams may want to promote drills surrounding each of these four situations rather than create tactics and drills around all seven kick types or certain zones of the field.

An example of an application of this analysis is utilising it in conjunction with a team sprint analysis to understand the range of contestability for a particular group of players, given a certain kick type or to prepare for a certain kicking outcome. This data can be utilised in conjunction with sprint velocity profiling to interpret a player's capability to contest kicks and what kick types are most contestable. For example, using clusters identified in this chapter and maximum velocities and tau values previously reported in literature for backs (Clavel et al., 2022; Duthie et al., 2006; Morin et al., 2019), the distance and gain capacity of players given different starting mechanisms can be calculated and is displayed in Figures 7.9a and 7.9b. This includes the distance and gain capacity of backs given a standing, walking, jogging and striding start.

These capacity lines run through both contestable clusters identified above, however, more of the ″slow″ contestable (light blue) cluster is deemed achievable compared to the ″fast″ contestable cluster (red). The dark blue ellipse illustrates the 90% confidence interval ellipse of kicks successfully collected by the kicking team, again with these capacity lines going through the ellipse. This suggests that from the starting place of the kick, not all kicks are contestable by the kicker.

However, it is not only the kicker who may look to contest a kick, linking to Figure 7.9b, where the clusters are calculated by gain (see Appendix D.4 for full results of gain cluster analysis). In this figure, the majority of the ″slow″ contestables are within a player's capacity. Some of the kicks within the ″fast″ contestables are still unachievable, possibly suggesting that a player may need to be travelling at a faster initial speed to reach these kicks. Most of the kicks that were in the successfully collected ellipse tend to be within the capacity of at least a striding start. These figures are also available for the forwards in Appendix D.5.

With this application, teams can begin to understand what is truly contestable by their current squad and how they can utilise this to drive conditioning programmes, tactical drills and in-game plays.




**(a)** Distance-time Plot

**(b)** Gain-time Plot

**Figure 7.9**

Comparison of distance-time and gain-time Plots for different starting mechanisms. The subplots show (a) the distance-time plot and (b) the gain-time plot, each with previous clusters of ″Fast″ and ″Slow″ Territorial (grey and green respectively), ″Fast″ and ″Slow″ Contestables (red and light blue) represented by the related coloured polygons. The dark blue polygons represent the 90% confidence ellipse of kicks successfully collected by the kicking team. The four lines in each plot identify the capacity for a back given the different starting mechanisms (green for standing, yellow for walking, orange for jogging, and red for striding start), based on tau and max values from literature (Clavel et al., 2022; Duthie et al., 2006).

### 7.5.4 Methodology

Collection time has been estimated within the study design of this chapter, by matching the clock times when a kick was made to the clock time when the next adjacent collection was made. This is a novel way to measure the collection time of a kick and has yet to be used in the literature, mostly as this area of research has not garnered attention from researchers at the current time. Traditionally, hang time has been analysed as a measure of ball kinematics in laboratory experiments, (Seo, Kobayashi et al., 2010; Seo, Yorita et al., 2010), rather than in actual gameplay kicking. However, hang time has been used colloquially in non-academic analysis of the game (Rugby-World, 2021). Collection time provides a slightly different approximation to this, for most kicks it is likely to be in a similar range, but with this computation, balls that bounce, or travel close to the ground can also be accounted for in the analysis.

Within rugby, there has been an increase in the use of technology to improve teams' understanding of the sport, and one relatively new area is the use of smart rugby balls. These rechargeable balls contain a tracking device that communicates with beacons around the stadium, allowing the movement of the ball to be tracked in 3D. This device is also able to differentiate between kick types and provides information similar to what has been estimated within this chapter and more, such as distance, hang time, speed and spin (BBC, 2023). This can also extend to other parts of the game, including passing and lineout analysis. This equipment may become a normal part of the performance kit used within elite teams in the future and may simplify the mechanism of analysis provided within this chapter. However, the overall principle of this analysis, in terms of understanding the spatiotemporal characteristics of kicks in different circumstances is still relevant and can be applied to data from alternative sources such as smart technology.

The analysis of distance-time may also be useful in other areas of the game, including passing, tackling and other tactical skills that require an element of time management to be successful. This analysis could be easily replicated using the same dataset but other key performance variables. Equally, this could be applied to other ball sports with detailed time XML analysis available and applied to individual athletes to understand their performance.

Clustering methods have been used in this chapter's results to analyse the data without using supervised labels. Centroid-based clustering has been used, in the form of K-Means clustering, however, other clustering algorithms are available, including hierarchical, density, distribution and grid methods. The benefit of K-Means clustering, in this case, is that it is not computationally extensive, meaning it can be repeated in a practical environment quickly compared to other methods (Morissette & Chartier, 2013).

## 7.6 Practical Applications

This chapter's results can be applied to rugby training and used to support kicking strategies within rugby. The summaries provided from kick types, zones and outcomes give context to teams around the demands of kicking. They hence can influence training, through tactical and physical performance strategies before match day.

This clustering terminology could be used within squads to simplify kicking strategies. Whilst the kicker will need to use a specific kick type, having a general approach to the four kick clusters may be beneficial for supporting players in terms of what approach can be used in a game and what the related job of an individual is to support that play. This methodology may also be useful at the club level to group opposition kicks into certain clusters to create responses to kick patterns individually.

## 7.7 Limitations

The use of video analysis data within this chapter has allowed the analysis of a large dataset of kicks across multiple teams in a season of the URC. Whilst this is beneficial in terms of dataset size, future studies may benefit from using new technology to analyse similar themes around kicking. For example, the use of smart rugby balls may provide improved detail and understanding of distance and speed, without reliance on video analysis. Another reason this technology may be beneficial is the discrepancy within $xy$ coordinates identified within the validity study of this thesis in Chapter 3. The vast majority of kicks were within 2 m of the original data provided by OPTA, however, these small changes may impact the distance results. This may be avoided with the use of newer technology.

Another key limitation of this chapter is that only one season of data has been analysed, indicating its relevance may decrease over time. However, certain areas of this research, namely the distance and collection time, may not change over time given the limits of human ability to kick, sprint and make decisions.

## 7.8 Conclusions

The aims of this chapter were to understand the speed, distance and collection time profiles of the different kick types, as well as to investigate the requirements in different circumstances on the field, and group kicks based on these values.

This analysis highlighted differences in collection time, speed and distance between kick types and zone, as well as in different circumstances on the field. These differences highlighted that there is a divide between long kicks (which could be described as territorial), and shorter kicks (described as possible attacking or contestable kicks). Outcomes tended to match this, with balls caught by the opposition being longer distanced on average, compared to those caught by the kicking team. Equally, when collecting players are able to return a kick or pass to a teammate to do this, it tended to be off the back of a longer distance kick. This result was supported by clustering analysis, which identified four main clusters. Two of these clusters had higher mean distances: one with a higher mean collection time and one with a lower mean collection time. The other two were noted by lower distances, with one cluster with a higher mean collection and one with a lower mean collection time. This suggests that kicks can be split into four key groups, ″fast″ and ″slow″ territorial kicks and ″fast″ and ″slow″ contestable kicks.

# 8 General Discussion

## 8.1 Introduction

The primary aim of this doctoral thesis was to investigate successful performance within rugby, with large scale event datasets from the United Rugby Championship. This includes analysis of success at the match, sequence and action level. Therefore the aims of this thesis were the following:

1. Understand key performance indicators associated with match outcomes in the United Rugby Championship. (Chapter 4)
2. Interpret how relative kicking influences matches at the sequence level. (Chapter 5)
3. Investigate whether differences exist in kicking tactics between winning and losing teams. (Chapter 6)
4. Assess the spatiotemporal characteristics of kicks to inform the physical demands of a successful kick chase. (Chapter 7)

This chapter aims to interpret these results and synthesise across the four experimental chapters to identify key themes. Furthermore, the strengths and limitations of this research will be examined and discussed, as well as areas for future development. Finally, the practical applications of the results will be summarised.

## 8.2 Summary of Results

The first aim of this thesis was to understand key performance indicators (PIs) associated with successful match outcomes within the United Rugby Championship (URC). This chapter identified that using relative data instead of isolated data improved model prediction accuracy. It was also established that utilising model simplification methods, in this case, Maximum Relevance, Minimum Redundancy, did not negatively impact model efficacy, allowing the simplification of outputs from modelling without sacrificing prediction accuracy. However, the key result from this chapter was the recognition of five key PIs associated with match outcome, that is relative values of kicks from hand, metres made, clean breaks, turnovers conceded and scrum penalties.

The leading key PI from the first study of this thesis was kicks from hand, and given its unintuitive link to success, it was the key area of interest for the rest of this thesis. The second study, Chapter 5, aimed to analyse kicks from hand at the sequence level, to understand whether they were linked to success at this level. This chapter identified that the majority of sequences only had a value of +1 kicks, signifying that teams only tended to complete one additional kick than their opposition at the sequence level. This demonstrates that additional relative kicks are built across many sequences within the game. These kicks were analysed in the context of the team in possession at the end of the sequence, with +1 kicks suggesting that teams are either regaining possession from kicks or kicking directly to touch. This chapter also established that increased kicking is linked to increases in neutral outcomes and decreases in both positive and negative outcomes. However, negative outcomes decreased at a faster rate than positive outcomes as kicks increase. With more detailed context, it was identified that most tries scored in kicking sequences were scored when the scoring team made additional kicks than their opposition.

The following study, Chapter 6, maintained analysis at the sequence level with the addition of spatial context to kicks given in the field, as well as the context of winning and losing teams. It was identified that kicks were not balanced across the field of play nor across kick types, with kicks in a team's own half more popular, as well as territorial, box and touch kicks. Results highlighted that winning teams kicked more across all kick types and zones of the field, however, when accounting for the number of kicks taken, the distribution of kicks was similar between both teams. There were limited differences in sequence outcomes containing different kick types between winning and losing teams, with winners only benefiting from significant improvements in sequence outcomes from red zone kicks. Decision trees displayed a greater context again, with winning teams benefiting from a higher proportion of tries scored in positive kicking sequences as well as lower proportion of tries conceded, and vice versa in losing teams.

The final study of this thesis, Chapter 7, aimed to examine kicks from hand at the action level and understand the spatiotemporal characteristics of the kicks previously analysed. This analysis highlighted differences in collection time, speed and distance between kick types and zones, as well as in different circumstances on the field. These differences highlighted that there is a divide between long kicks (which could be described as territorial), and shorter kicks (described as possible attacking or contestable kicks). Clustering analysis identified four main clusters. Two of these clusters had higher mean distances: one with a higher mean collection time and one with a lower mean collection time. The other two were noted by lower distances, with one cluster with a higher mean collection and one with a lower mean collection time. This suggests that kicks can be split into four key groups, which could be described as ″fast″ and ″slow″ territorial kicks alongside ″fast″ and ″slow″ contestable kicks.

## 8.3 Synthesis of Results and Key Themes

Relative data was a key theme throughout this thesis, predominantly in the first three studies. It was highlighted both in the first study and in previous research (Bennett et al., 2019, 2020), that relative data improves prediction accuracy in modelling. This concept continued within the second study, where relative kicking relationships appear clearer than those investigated via isolated data. In both chapters, the improvement from relative data may be linked to its symmetric nature, compared to the skewed values seen in isolated data. This could be considered similar to methods utilised when modelling association football scores, where both Maher (1982) and Dixon and Coles (1997) utilised the difference in two teams' relative attack and defence qualities. Relative kicking was also highlighted in the third study when the difference in frequencies across different kick types and zones was established, identifying a large increase in kicking in winning teams compared to their losing counterparts. This may mean this improvement can be extended into other areas of research into rugby, however, other studies have not established the same benefit from utilising relative data in lower levels of competition and the women's game (Mosey & Mitchell, 2020; Scott et al., 2023).

Another key theme across this thesis was the importance of attacking metrics. Firstly highlighted in Chapter 4, through the clean breaks and metres made PIs, the theme continued as the thesis examined kicking. It is clear that attacking metrics were a key part of success within this thesis as has been highlighted in other studies also, both at the match (Bennett et al., 2020; Bunker & Spencer, 2021; Mosey & Mitchell, 2020) and action level (den Hollander et al., 2016; Wheeler et al., 2010).

Within kicking, it is clear there was a link between both attacking kicks and success as highlighted in Chapter 6, as well as evidence of kicks being regathered (Chapters 5 and 7). Equally, the positioning of kicks is important, given the importance of red zone kicks highlighted in Chapter 6. Their link to attacking metrics is the proximity to an opposition try line. Positioning of kicking has been reported as critical by A. Hughes et al. (2017), who noted that kicks between opposition 22 m to 50 m were linked to success. In terms of this thesis, this is the area of the field just before the red zone. Equally, although not necessarily directly linked to attacking play, the two clusters with shorter kick distances, named as ″contestables″ may hint at the use of kicks for both regathering but also putting the opposition under pressure. For example, if the kicking team cannot regather the kick themselves, they may still be able to make a timely tackle and contest at the ruck. This contest may even lead to a turnover, linking back to one of the PIs identified in the first study and in other literature (Mosey & Mitchell, 2020).

However, it has also been identified within this thesis that these styles of kicks form a small number of the total kicks taken within matches (Chapter 6 and Chapter 7) in corroboration with what had been reported by Lazarczuk et al. (2020). This was first identified within Chapter 6 where low, chip, cross pitch and bomb kicks were a small portion of the total kicks taken in a season of matches in the URC. A similar result was established in Chapter 7, where shorter and quicker collected kicks displayed a low density across the spatiotemporal figure (Figure 7.1). The lack of shorter kicks and higher frequency of longer kicks hints at a larger concept that also spans different studies of this thesis, the importance of territory. First discussed within Chapter 5, this concept came to further light within the results of Chapter 6. Both the amount of +1 kicks given in context to the reference team, as well as a large amount of neutral outcomes (where a ball goes out of the field of play or a mark is called) illustrated as relative kicks increase, exhibits that kicking for territory must be a key part of kicks from hand within rugby.

This was developed further in Chapter 6, where territorial, box and touch kicks were highlighted as the most common kick types, as well as kicking most commonly taking place within a team's own half. Equally, this was further demonstrated when analysing the spatiotemporal values of kicking, with longer distance kicks identified in two of the clusters, with shorter and longer collection times in each cluster respectively. Rugby is an invasion game, so it is intuitive that territory is a key part of the game, and kicking gives a great opportunity to do this. A. Hughes et al. (2017) suggested that Men's rugby tends to favour a territory-based approach, and Bunker and Spencer (2021) also established that increased kicking metres are associated with winning match outcomes again suggesting a link to a territory-based game.

The development of performance questions and utilisation of big datasets is another motif of this thesis across all studies. Beginning from the literature surrounding this research area (Bennett et al., 2019; Watson et al., 2017), it was clear there was a limitation within previous research in terms of understanding the full breadth of performance from a team level to an individual level. This thesis aimed to develop a performance question, detailing results at different levels to give holistic understanding of a performance metric. Starting at the match level, this thesis uncovered the determinants of a successful match outcome, highlighting five PIs, including kicks from hand. From here, the remainder of the thesis focussed on kicks from hand and understanding their link to success at different detailed levels of the game. This includes utilising sequence and action level data, as well as increasing context given to the spatial characteristics of kicks. This allowed a thorough analysis across many different attributes and the practical applications of this research engage not only analysts, but also coaches, and strength and conditioning practitioners. The outputs from this thesis follow kicking from the match level, down to the sequence and then the individual levels, giving broad results that can be utilised in many ways.

Building frameworks for performance has been developed in different areas of sports research, including holistic physical performance (Turner et al., 2019), rugby match performance (Calder & Durbach, 2015) and rugby skill-specific performance (Hendricks et al., 2018). The former study provides a holistic understanding of what represents a ″fit″ player, and the latter two studies provide an understanding of players' overall contribution to a match and then build a framework for skill development. This is of interest, as these studies tend to cover similar themes seen across this thesis, analysing at the match and action level, therefore a combination of previous reports in the literature may be another way to build a holistic overview of performance itself.

An important theme across this thesis is the dichotomy of simplification and detailed context required within research into rugby, which could be called the simplicity-complexity trade-off. Firstly, within Chapter 4, modelling simplification methods were used to limit the number of PIs utilised in models, therefore shrinking the number of significant PIs in comparison to similar studies (Bennett et al., 2019, 2020). This allows simplification of messaging to ease practitioners' ability to implement change or monitor PIs in the future. This theme returns in the final experimental chapter, where clustering analysis provides simplification of kicking styles based on spatiotemporal characteristics. Ultimately, this chapter utilised simple data with many different contextual factors in the exploratory analysis, with the formal clustering analysis allowing for this to be interpreted on a simpler scale. This may be useful to practitioners when developing conditioning programmes, tactical decisions and even team selection.

On the contrary, the second and third experimental chapters began with simpler analysis, before giving greater consideration to context and detail of the results given. This was supported by understanding the detailed sequence outcomes, moving from positive, negative and neutral to context-based, with tries scored, penalties won and possession gained and their equivalent negative outcomes. This is in contrast to the simplification seen in other chapters and provides a greater understanding of results that may benefit practitioners in a different manner. Despite the additional context, it still allows for clear and coherent messaging.

The use of context is useful within rugby, given the complex nature of the game itself. This additional context gives a ″how″ to the results from each chapter and may assist in justifying the use of simpler measures. This has been discussed by den Hollander et al. (2018), insisting on the importance of the ″what″ and ″how″ studies, that is both understanding what is important to success in terms of video analysis and why it is important. This relates to the additional context which may give the ″why″ in the chapters of this thesis. Overall, the balance of context has been a key feature of this thesis, given the complexity of the datasets given and the increasing level of detail analysed throughout the chapters.

When the literature was reviewed in the second chapter of this thesis, the discussion of complexity within the area of performance analysis was discussed. This included reference to the increasing complexity caused by increases in the granularity of different measurements, including outcome, temporal and spatial measures. Throughout this thesis, each chapter has aimed to gain further insights from the previous chapter by increasing the granularity of both outcome and temporal measures, and this has been plotted in Figure 8.1. This figure illustrates the increase in both outcome and temporal granularity, but it is important to note that these changes do not necessarily both increase in each chapter. However, the thesis does take complexity from the simplest level, the categorical outcome at the match level, to the more complex, continuous outcome at the action level. Equally, these studies have also increased granularity in spatial measurements, with Chapter 4 and 5 utilising no specific spatial reference, Chapters 6 analysing spatial zones and finally Chapter 7 extracting specific $x$ and $y$ coordinates. This is displayed visually in Figure 8.2

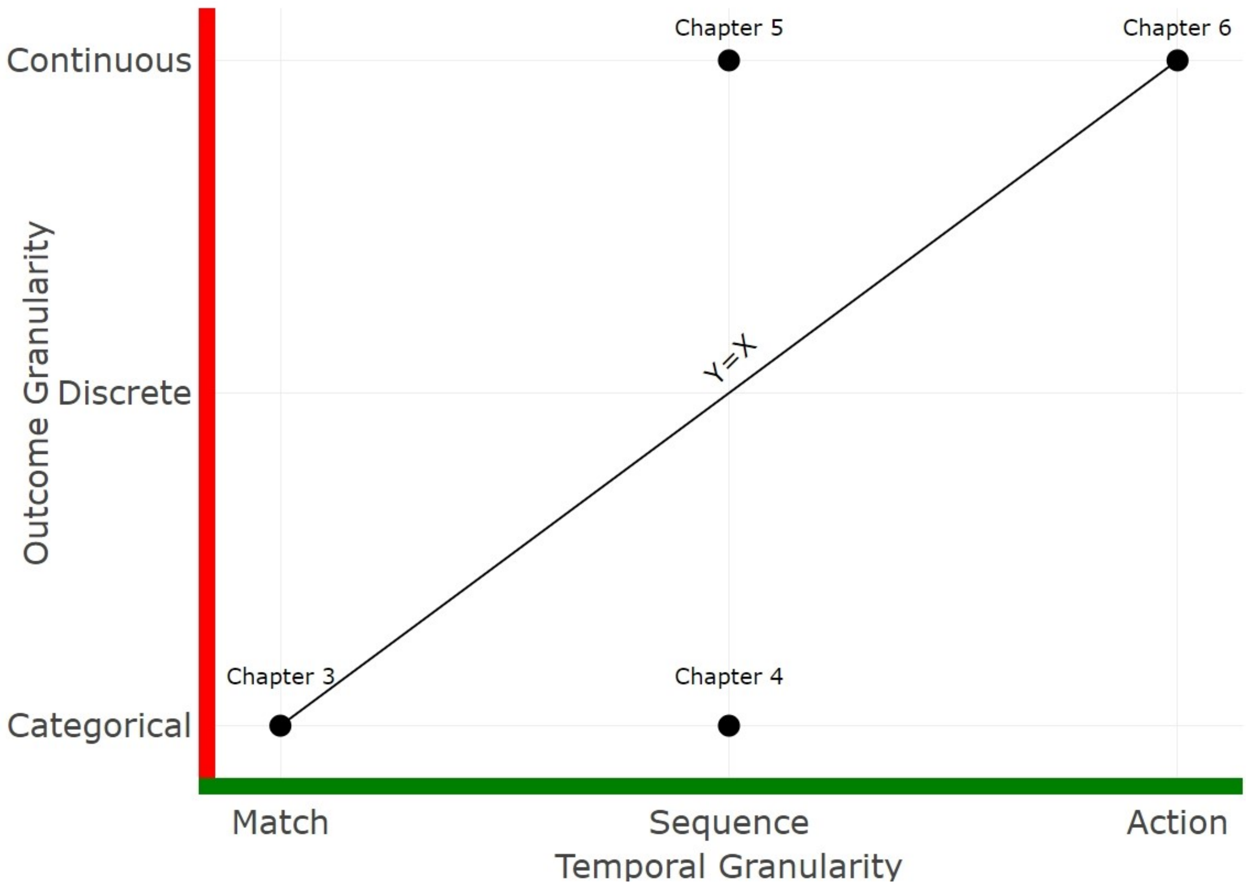



**Figure 8.1**
2D Complexity space, with temporal granularity represented on the $x$-axis and outcome granularity represented on the $y$-axis. The $x$=$y$ line represents an equal increase in granularity across both axes. Each experimental chapter of this thesis has been placed on the appropriate part of the figure.

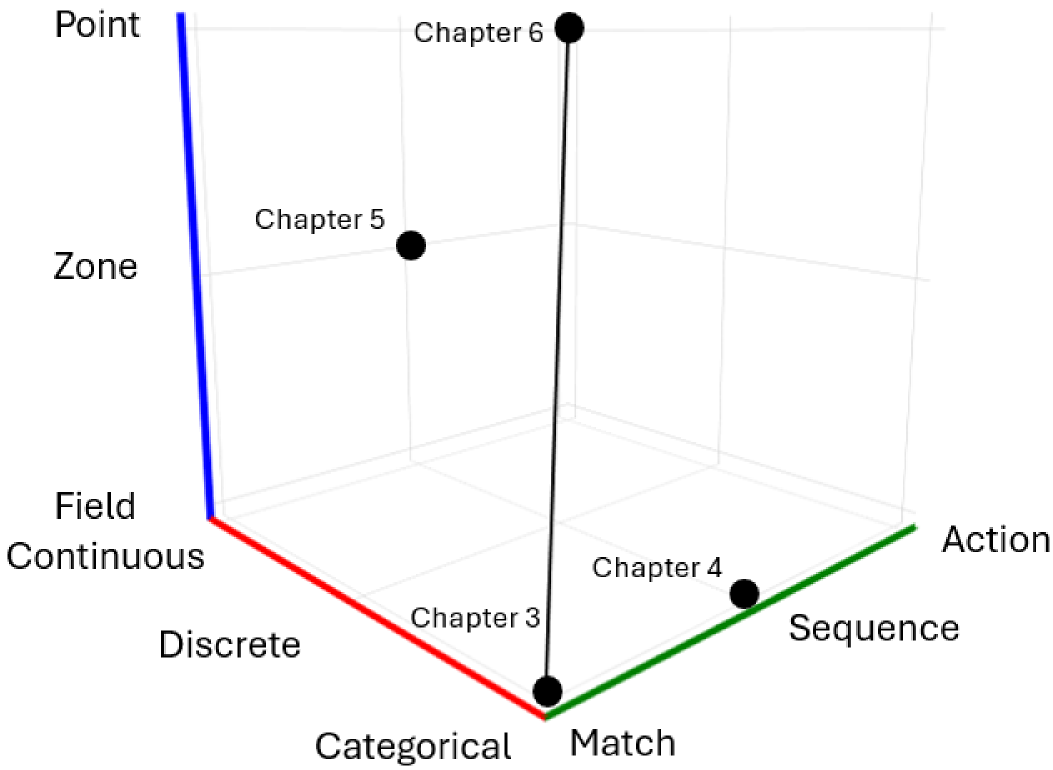



**Figure 8.2**
3D Complexity space, with temporal granularity represented on the $x$-axis, outcome granularity represented on the $y$-axis and spatial granularity represented on the $z$-axis. The $x$=$y$=$z$ line represents an equal increase in granularity across all axes. Each experimental chapter of this thesis has been placed on the appropriate part of the figure.

## 8.4 Strengths and Limitations

A clear strength of this thesis was its ability to analyse at different levels of detail within a match of rugby. The analysis provided was sequential and based on emergent results from each chapter to ensure maximal understanding of what is required to inform further insights at each stage of the research. This allowed appropriate dissemination of results at each level and the link between each chapter. This concept of design could be utilised on other KPIs and in other competitions to define and understand performance questions in a holistic manner. It could also be applied to other field or court-based sports.

Another strength of this research was the use of a larger dataset from a single season. Whilst

Chapter 4 highlighted that there are significant changes season to season within rugby, the ability to utilise action data allowed the creation of a large dataset for analysis at the detailed level. This is beneficial as larger datasets are preferable in statistical analysis, but also because the data covered 16 teams within the competitions, meaning a magnitude of playing styles, player selections and different parts of the season could be included, avoiding bias to a certain style of play.

Given the dataset size, there was also the opportunity to use a selection of statistical methods within this thesis, which included hypothesis testing, supervised and unsupervised learning. This provided a comprehensive analysis across different methodologies and allowed the flexibility of data with different characteristics, including different assumptions and data types. Equally, it permitted novelty in some methods within research in rugby, alongside familiarity and corroboration with research already existing in this space.

In contrast, there were limitations and challenges related to the research put forward within this thesis. The first key limitation was the choice to limit this thesis to one of the five key PIs identified in the first study. This was unavoidable due to the level of detail analysed within this thesis, and although kicking was specifically chosen due to its unintuitive link to success at the match level, there is the opportunity for analysis into the other four PIs. This thesis has provided a structure to influence future analysis into metres made, clean breaks, turnovers conceded and scrum penalties, allowing a similar analysis at both the match, sequence and action level. This would be an area of interest for future research. Equally, the relationships between the PIs are also an area of interest, given their possible links to each other previously highlighted within this thesis and other research (Scott et al., 2023).

Another limitation that has been alluded to was the simplicity-complexity tradeoff. Throughout this thesis, there have been methods utilised to simplify messaging from the output of the analysis, but there is a small cost of the loss of information. Additional information may highlight further understanding of the named performance questions, but it can be difficult to analyse in the first place. However, in parts of this thesis, additional context has been added post hoc to enhance results and give further knowledge to support practical decision-making. This illustrates the requirement to manage the simplicity-complexity tradeoff, so to ensure optimal applicability of results without losing key context needed to ensure they can be understood accurately. This can also be discussed in the context of data selection. For example, within this thesis, all teams in the URC were included within datasets, which can be considered a strength given the breadth of playing styles available. However, by not analysing in further detail, on a team by team level, some additional results may be missed in a mixed dataset. This limitation leads to thoughts for future research, with a need to examine and interpret playing styles and whether these impact PIs and other kicking metrics.

Moreover, playing styles may also be linked to different competitions, playing levels, and parts of the world. This thesis has focussed on the URC, a global club-level competition, featuring teams from Ireland, Italy, Scotland, South Africa and Wales, so its generalisability to other competitions, specifically the international level, is unknown. The literature has suggested that few key PIs can be utilised in multiple competitions to understand performance (Watson et al., 2017), however, one PI that did describe success across many competitions was kicking. Without future research into the implications of kicking in other competitions, it is difficult to corroborate whether the results of this thesis are generalisable to other competitions and levels of rugby. However, the methodologies from this thesis, from both a data curation and statistical perspective, are usable in all competitions where event data is available, including in other team-based field sports.

Finally, this thesis has solely investigated video analysis datasets, at the match, sequence and action level. However, within the elite game, data is available from many other sources, including but not limited to, GPS, strength testing and wellbeing data, which could offer other insights alone and in conjunction with video analysis data. To build an even more comprehensive view into performance utilising big data, future research should look to combine multiple datasets to form and answer performance questions. A key example from this thesis would be the inclusion of match-day GPS to further interpret the spatiotemporal characteristics of kicking.

## 8.5 Conclusions

To conclude, this thesis sought to understand the key performance indicators associated with match outcomes and interpret how relative kicking influences matches at the sequence level. It also aimed to interpret whether different kicking tactics exist between winning and losing teams and assess the spatiotemporal characteristics associated with kicks to inform a successful kick chase. Results indicated the importance of relative data and highlighted that relative kicking, metres made, clean breaks, turnovers conceded and scrum penalties were associated with match outcome. It was also identified that most sequences had +1 relative kicks, and increased relative kicking was associated with increased neutral outcomes and decreased negative outcomes. The distribution of kicking types and zones was similar between winning and losing teams when corrected for the number of kicks, however winning teams outkicked losing teams in every type and zone. Red zone kicks were the only area where winners had significantly better sequence outcomes. Finally, utilising spatiotemporal characteristics, kicks could be separated into four key clusters, including ″fast″ and ″slow″ contestables and ″fast″ and ″slow″ territorials.

Key themes across this thesis included the use of relative data at both the match and sequence level, promoting model efficacy and improved interpretation of success. Attacking metrics were deemed important across many chapters of this thesis, in and out of the context of kicking, both alone and in combination with territorial tactics. Furthermore, the use of big data and increased detail in analysis has been illustrated throughout the chapters of this thesis, with results aiming to produce simplified outputs for practical application. The simplicity-complexity tradeoff was explored throughout, with some areas of this research benefiting from additional context and some benefiting from simplification methods. Overall, this thesis provided increased complexity in analysis in each chapter.

Strengths of this research were the use of large datasets, including many teams within one competition. Equally, the development of a conceptual design to analyse performance at multiple levels was a key strength, as well as the variety of methods utilised, driving a flexible approach to analysis. In contrast, a key limitation was the use of a single competition, as well as the lack of analysis into the other key PIs identified in the first study.

## 8.6 Future Research Opportunities

The results of this thesis provide scope for further research utilising video analysis event data to understand performance, by investigating the following research aims:

- Examine the sequence and action level impact of relative metres made, clean breaks, turnovers conceded and scrum penalties.
- Determine whether the distribution of kick types, zones and spatiotemporal characteristics is similar in other major world competitions, including at the international level.
- Incorporate GPS into spatiotemporal understanding of kicking to interpret worst-case scenarios and other traditional conditioning metrics.

## 8.7 Summary of Practical Applications

The summary of the key practical applications from the experimental chapters of this thesis are as follows.

- Utilising relative performance indicators rather than traditional values can give coaches and analysts a better understanding of success, specifically the five identified in this thesis: kicks from hand, metres made, clean breaks, turnovers conceded and scrum penalties. These can be monitored across the season, or during a match itself, for both a coach's own team and as part of opposition analysis. This application was utilised between 2021/22 - 2023/24 season for our project partner, the Ospreys. (Chapter 4)
- Understanding that most sequences only contain +1 relative kicks, can be utilised by coaches to drive decision-making in the game. In multi-kick sequences, teams should be encouraged to make the final kick to promote +1 relative kicks, leading to territorial gain or even tries scored. (Chapter 5)
- With the distribution of kick types and zones similar between winning and losing teams when accounting for the number of kicks, it is clear that winning teams should aim to kick more across all zones of the field and kick types. In terms of improved outcomes, the fact that winning teams kicked better in the red zone and more of their positive outcomes were linked to tries scored, suggests that coaches should create tactics that include attacking kicks in this valuable area of the field. These results were utilised in discussions with coaches about kicking opportunities in games with the Ospreys. (Chapter 6)
- Both the frequency of kicks in each zone and kick types (Chapter 6), alongside the spatiotemporal characteristics (Chapter 7) can be utilised by strength and conditioning coaches to interpret the kicking load, as well as build drills and other programmes that prepare players to reach and maintain these speeds on match day. The Ospreys utilised kick distances and collection time to design drills within the training programme to prepare players for match-day kicking.

# A Appendix A

## A.1 Approval Letters

**LEAD APPLICANT NAME:** Georgia Scott
**DISCIPLINE/DEPARTMENT:** SPEX
**PROJECT TITLE:** THE APPLICATION OF ADVANCED DATA ANALYTICS TO PREDICT RUGBY MATCH OUTCOME IN THE PRO14 LEAGUE
**APPLICATION REFFERENCE NUMBER:** Georgia_Scott_31-08-21

Swansea University
Prifysgol Abertawe

**Date of review board:** September
**Committee members in attendance:** Chairs

**Date:** Thursday 16th September

Dear Georgia,

Thank you for your recent ethics application.

This decision letter is to inform you that the ethics application for the above titled project has been reviewed and approved. The ethical approval number for this application is GS_31-08-21 approved from 16/09/21– end of approval 30/06/22. Please see reviewer document for more information.

This letter is for Swansea University, College of Engineering Research Ethics and Governance approval only. Local Health and Safety, in addition to appropriate risk assessment guidelines are required separate to this approval, unless otherwise stated herein, and must be adhered to.

Associated researchers must not deviate from the approved protocol or extend beyond the approval end date. Any desired deviations or approval date extensions are subject to the ethical approval amendment process. Upon completion of the approved project researchers responsible for this application must submit a final (short) statement to the ethical committee stating the completion of the project, unless a time extension is being requested through the amendment process.

Any significant un-anticipated adverse effects/events (i.e. not those predicted and stated in section 8 of the ethics application form) must be reported to the Ethics committee upon researcher realisation (email: coe-researchethics@swansea.ac.uk; with the subject title including the study approval number followed by "Adverse Effects/Events").

If you have any further questions relating to your application, please contact: coe-researchethics@swansea.ac.uk.

Please keep note of your approval number for future reference and correspondence relating to this application.

Best of luck with your research.

Warm regards,

Aynsley Fagan

**(on behalf of the College of Engineering Research Ethics and Governance Chair)**

---

**College of Engineering Ethics and Governance Committee Administrator**
**College of Engineering | Y Coleg Peirianneg**
**Swansea University | Prifysgol Abertawe**
**Fabian Way | Ffordd Fabian Crymlyn Burrows**
**Swansea | Abertawe**
**Wales | Cymru**
**SA1 8EN**

**Email:** coe-researchethics@swansea.ac.uk.

**Figure A1**
Approval letter confirming ethical approval for experimental study within Chapter 4.

Dear Swansea University, College of Engineering Ethics Chair,

RE: THE APPLICATION OF ADVANCED DATA ANALYTICS TO PREDICT RUGBY MATCH OUTCOME IN THE PRO14 LEAGUE – permission to collect, analyse and publish OPTA, GPS and Wellbeing Data From Ospreys

I am writing in support of the above study, which is being undertaken by Swansea University, in collaboration with Ospreys under the direction of Dr Rowan Brown, Professor Liam Kilduff, Dr Mark Waldron and Dr Neil Bezodis and Georgia Scott.

This is original and high-impact research for elite rugby union and will help us to better understand the factors that influence match outcome and success in the PRO14 (now known as United 16).

The club give the abovementioned personnel permission to receive historical player data required for the purpose of completing this research project, under the assumption of relevant GDPR compliance and institutional ethical approval.

I also consent to the confidential and anonymous publication and dissemination of this data. This includes all anonymised GPS training data, and any additional physical data, collected between 2017-2022 and all future data collected during the duration of the project until the end date in 2024.

Kind regards,

NAME OF CLUB PERSONNEL: SIMON CHURCH

E-SIGNATURE: [redacted]

CONTACT INFORMATION: [redacted]

**Figure A2**
Approval letter from Ospreys for use of data throughout the thesis

## A.2 Performance Indicators Definitions

**Table A1**
Super Scout Rugby definitions of performance indicators for the Attack Group.

| Performance Indicator | Definition |
|---|---|
| Carries | A player touching the ball has deemed to make a carry if they have made an obvious attempt to engage the opposition with the ball in hand. |
| Metres Made | Metres made by a player touching the ball, calculated from the gain line. |
| Defenders Beaten | The ball carrier has made a defending player miss a tackle through evasive manoeuvres, physical dominance or good running line. A ball carrier is awarded one defender beaten for every opponent evaded. |
| Offloads | The player attempts a passes while in a tackle. |
| Passes | A player has attempted to throw the ball with purpose to a teammate. |
| Kicks from Hand | A player has attempted to strike the ball with their foot during play. |
| Clean Breaks | A missed tackle lead directly to a clean break by the attacker. |

**Table A2**
Super Scout Rugby definitions of performance indicators in the Defence, Ruck and Turnover Group.

| Performance Indicator | Definition |
|---|---|
| Tackles | A player has attempted to halt the progress or dispossess an opponent in possession of the ball. |
| Missed Tackles | A tackle is deemed missed when a player has failed to affect a tackle on an opposition player when they were in a reasonable position to make the tackle. |
| Turnovers Won | The team wins possession from the opposition in general play. This can be from an interception, ruck or maul turnover (Jackal), a handling error or a charged down kick. |
| Turnovers Conceded | A player has made an error which leads to the opposition gaining possession of the ball, either in open play or in the form of a scrum/lineout. |
| Rucks Won | A phase of play where one or more players from each team, who are on their feet, in physical contact, close around the ball on the ground is won by the attacking team. |
| Rucks Lost | A phase of play where one or more players from each team, who are on their feet, in physical contact, close around the ball on the ground is lost by the attacking team. |

**Table A3**
Super Scout Rugby definitions of performance indicators in the Set Piece Group.

| Performance Indicator | Definition |
|---|---|
| Lineouts Won | The attacking team have secured the ball at the lineout. |
| Lineouts Lost | The attacking team have lost the ball to the opposition at the lineout. |
| Scrums Won | The attacking team have secured the ball at the scrum. |
| Scrums Lost | The attacking team have lost the ball to the opposition at the scrum. |

**Table A4**
Super Scout Rugby definitions of performance indicators in the Penalties and Infringements Group.

| Performance Indicator | Definition |
|---|---|
| Penalties Conceded | When a player or team has been deemed to be breaking the laws of the game by the referee, where a full arm penalty is the appropriate sanction. |
| Free Kicks | When a player or team has been deemed to be breaking the laws of the game by the referee, where only a free kick is the appropriate sanction. |
| Scrum Penalties | The player has committed an offence at the scrum where a penalty is the appropriate sanction. |
| Lineout Penalties | The player has committed an offence at the lineout where a penalty is the appropriate sanction. |
| Tackle/Ruck/Maul Penalties | The player has committed an offence within a tackle, ruck or maul where a penalty is the appropriate sanction. |
| General Play Penalties | The player has committed an offence in general play where a penalty is the appropriate sanction. |
| Control Penalties | The player has committed an offence which is considered foul play, has argued with an official or has deliberately knocked on a ball where a penalty is the appropriate sanction. |

**Table A5**
Super Scout Rugby definitions of Yellow and Red Card performance indicators.

| Performance Indicator | Definition |
|---|---|
| Yellow Cards | A player receives a yellow card from the referee because of a penalty infringement, such as foul play or repeated infringements. |
| Red Cards | A player receives a red card from the referee because of a penalty infringement, such as foul play, repeated infringements, or two previous yellow cards. |

## A.3 Normality Testing

**Table A6**
Shapiro test statistics and $p$ values for both the isolated and relative datasets of the 2017/18 season. All numerical variables were tested and a significance level of 5% was used.

| Season | PI | Isolated Statistic Value | Isolated $p$ Value | Relative Statistic Value | Relative $p$ Value |
|---|---|---|---|---|---|
| S17 | Carries | 0.99 | 0.00 | 1.00 | .993 |
| S17 | Metres Made | 0.98 | 0.00 | 1.00 | .977 |
| S17 | Defenders Beaten | 0.98 | 0.00 | 0.99 | .027 |
| S17 | Offloads | 0.97 | 0.00 | 0.99 | .142 |
| S17 | Passes | 0.98 | 0.00 | 0.99 | .389 |
| S17 | Tackles | 0.96 | 0.00 | 0.99 | .327 |
| S17 | Missed Tackles | 0.98 | 0.00 | 0.99 | .027 |
| S17 | Turnovers Conceded | 0.98 | 0.00 | 0.99 | .095 |
| S17 | Kicks from Hand | 0.98 | 0.00 | 0.99 | .011 |
| S17 | Clean Breaks | 0.97 | 0.00 | 1.00 | .891 |
| S17 | Turnovers Won | 0.98 | 0.00 | 0.99 | .075 |
| S17 | Lineouts Won | 0.99 | 0.00 | 0.99 | .035 |
| S17 | Lineouts Lost | 0.88 | 0.00 | 0.97 | .000 |
| S17 | Scrums Won | 0.97 | 0.00 | 0.99 | .024 |
| S17 | Scrums Lost | 0.69 | 0.00 | 0.93 | .000 |
| S17 | Rucks Won | 0.97 | 0.00 | 1.00 | .928 |
| S17 | Rucks Lost | 0.94 | 0.00 | 0.98 | .002 |
| S17 | Penalties Conceded | 0.99 | 0.00 | 0.99 | .123 |
| S17 | Free Kicks | 0.75 | 0.00 | 0.90 | .000 |
| S17 | Scrum Penalties | 0.89 | 0.00 | 0.98 | .000 |
| S17 | Lineout Penalties | 0.54 | 0.00 | 0.81 | .000 |
| S17 | Tackle/Ruck/Maul Penalties | 0.97 | 0.00 | 0.98 | .001 |
| S17 | General Play Penalties | 0.92 | 0.00 | 0.97 | .000 |
| S17 | Control Penalties | 0.84 | 0.00 | 0.96 | .000 |
| S17 | Yellow Cards | 0.64 | 0.00 | 0.88 | .000 |
| S17 | Red Cards | 0.15 | 0.00 | 0.29 | .000 |

**Table A7**

Shapiro test statistics and $p$ values for both the isolated and relative datasets of the 2018/19 season. All numerical variables were tested and a significance level of 5% was used.

| Season | PI | Isolated Statistic Value | Isolated $p$ Value | Relative Statistic Value | Relative $p$ Value |
|---|---|---|---|---|---|
| S18 | Carries | 0.99 | .014 | 1.00 | .904 |
| S18 | Metres Made | 0.98 | .000 | 1.00 | .494 |
| S18 | Defenders Beaten | 0.97 | .000 | 0.99 | .390 |
| S18 | Offloads | 0.93 | .000 | 0.97 | .000 |
| S18 | Passes | 0.99 | .022 | 0.99 | .205 |
| S18 | Tackles | 0.98 | .000 | 1.00 | .825 |
| S18 | Missed Tackles | 0.97 | .000 | 0.99 | .390 |
| S18 | Turnovers Conceded | 0.98 | .001 | 0.99 | .241 |
| S18 | Kicks from Hand | 0.96 | .000 | 0.99 | .281 |
| S18 | Clean Breaks | 0.94 | .000 | 0.98 | .001 |
| S18 | Turnovers Won | 0.98 | .000 | 0.98 | .003 |
| S18 | Lineouts Won | 0.99 | .004 | 0.99 | .313 |
| S18 | Lineouts Lost | 0.86 | .000 | 0.96 | .000 |
| S18 | Scrums Won | 0.98 | .000 | 0.99 | .022 |
| S18 | Scrums Lost | 0.68 | .000 | 0.92 | .000 |
| S18 | Rucks Won | 0.98 | .000 | 1.00 | .752 |
| S18 | Rucks Lost | 0.96 | .000 | 0.98 | .001 |
| S18 | Penalties Conceded | 0.97 | .000 | 0.99 | .065 |
| S18 | Free Kicks | 0.72 | .000 | 0.90 | .000 |
| S18 | Scrum Penalties | 0.86 | .000 | 0.98 | .001 |
| S18 | Lineout Penalties | 0.62 | .000 | 0.86 | .000 |
| S18 | Tackle/Ruck/Maul Penalties | 0.97 | .000 | 0.99 | .007 |
| S18 | Gen Play Penalties | 0.88 | .000 | 0.97 | .000 |
| S18 | Control Penalties | 0.79 | .000 | 0.92 | .000 |
| S18 | Yellow Cards | 0.65 | .000 | 0.89 | .000 |
| S18 | Red Cards | 0.19 | .000 | 0.37 | .000 |

**Table A8**

Shapiro test statistics and $p$ values for both the isolated and relative datasets of the 2019/20 season. All numerical variables were tested and a significance level of 5% was used.

| Season | PI | Isolated Statistic Value | Isolated $p$ Value | Relative Statistic Value | Relative $p$ Value |
|---|---|---|---|---|---|
| S19 | Carries | 0.97 | .000 | 0.99 | .617 |
| S19 | Metres Made | 0.92 | .000 | 0.98 | .003 |
| S19 | Defenders Beaten | 0.95 | .000 | 0.99 | .078 |
| S19 | Offloads | 0.92 | .000 | 0.94 | .000 |
| S19 | Passes | 0.98 | .025 | 1.00 | .953 |
| S19 | Tackles | 0.97 | .000 | 1.00 | .789 |
| S19 | Missed Tackles | 0.95 | .000 | 0.99 | .083 |
| S19 | Turnovers Conceded | 0.98 | .020 | 0.99 | .112 |
| S19 | Kicks from Hand | 0.98 | .005 | 1.00 | .920 |
| S19 | Clean Breaks | 0.89 | .000 | 0.97 | .000 |
| S19 | Turnovers Won | 0.94 | .000 | 0.99 | .111 |
| S19 | Lineouts Won | 0.99 | .036 | 0.99 | .460 |
| S19 | Lineouts Lost | 0.90 | .000 | 0.98 | .008 |
| S19 | Scrums Won | 0.98 | .002 | 0.98 | .005 |
| S19 | Scrums Lost | 0.62 | .000 | 0.87 | .000 |
| S19 | Rucks Won | 0.96 | .000 | 0.99 | .550 |
| S19 | Rucks Lost | 0.92 | .000 | 0.98 | .021 |
| S19 | Penalties Conceded | 0.98 | .010 | 0.99 | .173 |
| S19 | Free Kicks | 0.75 | .000 | 0.92 | .000 |
| S19 | Scrum Penalties | 0.88 | .000 | 0.97 | .000 |
| S19 | Lineout Penalties | 0.61 | .000 | 0.85 | .000 |
| S19 | Tackle/Ruck/Maul Penalties | 0.96 | .000 | 0.98 | .011 |
| S19 | General Play Penalties | 0.91 | .000 | 0.97 | .000 |
| S19 | Control Penalties | 0.87 | .000 | 0.96 | .000 |
| S19 | Yellow Cards | 0.72 | .000 | 0.90 | .000 |
| S19 | Red Cards | 0.26 | .000 | 0.49 | .000 |

**Table A9**
Shapiro test statistics and $p$ values for both the isolated and relative datasets of the 2020/21 season. All numerical variables were tested and a significance level of 5% was used.

| Season | PI | Isolated Statistic Value | Isolated $p$ Value | Relative Statistic Value | Relative $p$ Value |
|---|---|---|---|---|---|
| S20 | Carries | 0.99 | .082 | 1.00 | .824 |
| S20 | Metres Made | 0.98 | .002 | 1.00 | .867 |
| S20 | Defenders Beaten | 0.95 | .000 | 0.99 | .501 |
| S20 | Offloads | 0.93 | .000 | 0.98 | .005 |
| S20 | Passes | 0.99 | .070 | 1.00 | .800 |
| S20 | Tackles | 0.98 | .016 | 0.99 | .170 |
| S20 | Missed Tackles | 0.95 | .00 | 0.99 | .501 |
| S20 | Turnovers Conceded | 0.99 | .052 | 0.99 | .079 |
| S20 | Kicks from Hand | 0.99 | .160 | 1.00 | .805 |
| S20 | Clean Breaks | 0.94 | .000 | 0.97 | .000 |
| S20 | Turnovers Won | 0.97 | .001 | 0.98 | .027 |
| S20 | Lineouts Won | 0.98 | .022 | 0.98 | .004 |
| S20 | Lineouts Lost | 0.90 | .000 | 0.97 | .001 |
| S20 | Scrums Won | 0.96 | .000 | 0.98 | .003 |
| S20 | Scrums Lost | 0.70 | .000 | 0.89 | .000 |
| S20 | Rucks Won | 0.98 | .005 | 0.99 | .347 |
| S20 | Rucks Lost | 0.95 | .000 | 0.98 | .019 |
| S20 | Penalties Conceded | 0.97 | .000 | 0.98 | .023 |
| S20 | Free Kicks | 0.76 | .000 | 0.87 | .000 |
| S20 | Scrum Penalties | 0.87 | .000 | 0.96 | .000 |
| S20 | Lineout Penalties | 0.67 | .000 | 0.89 | .000 |
| S20 | Tackle/Ruck/Maul Penalties | 0.98 | .002 | 0.98 | .005 |
| S20 | General Play Penalties | 0.91 | .000 | 0.96 | .000 |
| S20 | Control Penalties | 0.85 | .000 | 0.95 | .000 |
| S20 | Yellow Cards | 0.77 | .000 | 0.89 | .000 |
| S20 | Red Cards | 0.28 | .000 | 0.53 | .000 |

## A.4 Season Differences - Isolated Data

**Table A10**
Kruskal Wallis testing of season comparisons. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Degrees of Freedom | $\chi^2$ | $p_{adj}$ |
|---|---|---|---|
| Carry | 3 | 0.43 | 1.00 |
| Metres Made | 3 | 40.68 | .000 |
| Defender Beaten | 3 | 62.14 | .000 |
| Offloads | 3 | 18.63 | .008 |
| Passes | 3 | 64.55 | .000 |
| Tackles | 3 | 46.24 | .000 |
| Missed Tackles | 3 | 12.06 | .187 |
| Turnovers Conceded | 3 | 18.59 | .009 |
| Kicks from Hand | 3 | 41.07 | .000 |
| Clean Breaks | 3 | 45.41 | .000 |
| Turnovers Won | 3 | 33.95 | .000 |
| Lineouts Won | 3 | 19.68 | .005 |
| Lineouts Lost | 3 | 12.59 | .146 |
| Scrums Won | 3 | 9.36 | .648 |
| Scrums Lost | 3 | 8.43 | .987 |
| Rucks Won | 3 | 3.40 | 1.00 |
| Rucks Lost | 3 | 13.79 | .083 |
| Penalties Conceded | 3 | 10.59 | .369 |
| Free Kicks | 3 | 40.98 | .000 |
| Scrum Penalties | 3 | 4.43 | 1.00 |
| Lineout Penalties | 3 | 1.70 | 1.00 |
| Tackle/Ruck/Maul Penalties | 3 | 12.11 | .183 |
| General Play Penalties | 3 | 48.19 | .000 |
| Control Penalties | 3 | 16.32 | .025 |
| Yellow Cards | 3 | 2.89 | 1.00 |
| Red Cards | 3 | 23.34 | .001 |

**Table A11**
Dunn testing for season comparison of attack group performance indicators, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Season Pair | $z$ | $p_{adj}$ |
|---|---|---|---|
| Carry | S17 - S18 | -1.48 | .831 |
| | S17 - S19 | 2.72 | .039 |
| | S18 - S19 | 4.06 | .000 |
| | S17 - S20 | 4.46 | .000 |
| | S18 - S20 | 5.77 | .000 |
| | S19 - S20 | 1.66 | .587 |
| Metres Made | S17 - S18 | 0.99 | 1.00 |
| | S17 - S19 | 6.12 | .000 |
| | S18 - S19 | 5.23 | .000 |
| | S17 - S20 | 5.81 | .000 |
| | S18 - S20 | 4.94 | .000 |
| | S19 - S20 | -0.17 | 1.00 |
| Defender Beaten | S17 - S18 | -1.77 | .463 |
| | S17 - S19 | -1.16 | 1.00 |
| | S18 - S19 | 0.43 | 1.00 |
| | S17 - S20 | 2.53 | .069 |
| | S18 - S20 | 4.09 | .000 |
| | S19 - S20 | 3.38 | .004 |
| Offload | S17 - S18 | 3.36 | .005 |
| | S17 - S19 | 6.08 | .000 |
| | S18 - S19 | 3.04 | .014 |
| | S17 - S20 | 7.16 | .000 |
| | S18 - S20 | 4.18 | .000 |
| | S19 - S20 | 1.11 | 1.00 |
| Pass | S17 - S18 | 0.74 | 1.00 |
| | S17 - S19 | 5.10 | .000 |
| | S18 - S19 | 4.42 | .000 |
| | S17 - S20 | 5.13 | .000 |
| | S18 - S20 | 4.47 | .000 |
| | S19 - S20 | 0.13 | 1.00 |
| Kicks from Hand | S17 - S18 | 0.22 | 1.00 |
| | S17 - S19 | -2.49 | .076 |
| | S18 - S19 | -2.70 | .042 |
| | S17 - S20 | -5.83 | .000 |
| | S18 - S20 | -6.03 | .000 |
| | S19 - S20 | -3.12 | .011 |
| Clean Breaks | S17 - S18 | -0.67 | 1.00 |
| | S17 - S19 | 2.91 | .022 |
| | S18 - S19 | 3.52 | .003 |
| | S17 - S20 | 4.44 | .000 |
| | S18 - S20 | 5.04 | .000 |
| | S19 - S20 | 1.47 | .845 |

**Table A12**

Dunn testing for season comparison of defence, ruck and turnover group performance indicators, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Season Pair | $z$ | $p_{adj}$ |
|---|---|---|---|
| Tackle | S17 - S18 | -3.22 | .008 |
| | S17 - S19 | -0.72 | 1.00 |
| | S18 - S19 | 2.20 | .168 |
| | S17 - S20 | -0.38 | 1.00 |
| | S18 - S20 | 2.48 | .080 |
| | S19 - S20 | 0.30 | 1.00 |
| Missed Tackle | S17 - S18 | -1.77 | .463 |
| | S17 - S19 | -1.15 | 1.00 |
| | S18 - S19 | 0.44 | 1.00 |
| | S17 - S20 | 2.52 | .069 |
| | S18 - S20 | 4.09 | .000 |
| | S19 - S20 | 3.37 | .004 |
| Turnovers Conceded | S17 - S18 | 3.82 | .001 |
| | S17 - S19 | 4.32 | .000 |
| | S18 - S19 | 0.87 | 1.00 |
| | S17 - S20 | 6.03 | .000 |
| | S18 - S20 | 2.64 | .049 |
| | S19 - S20 | 1.65 | .589 |
| Turnovers Won | S17 - S18 | 1.16 | 1.00 |
| | S17 - S19 | 4.17 | .000 |
| | S18 - S19 | 3.12 | .011 |
| | S17 - S20 | 2.54 | .066 |
| | S18 - S20 | 1.51 | .780 |
| | S19 - S20 | -1.42 | .930 |
| Rucks Won | S17 - S18 | -2.06 | .233 |
| | S17 - S19 | 1.16 | 1.00 |
| | S18 - S19 | 3.02 | .015 |
| | S17 - S20 | 1.36 | 1.00 |
| | S18 - S20 | 3.18 | .009 |
| | S19 - S20 | 0.21 | 1.00 |
| Rucks Lost | S17 - S18 | -0.13 | 1.00 |
| | S17 - S19 | 2.44 | .089 |
| | S18 - S19 | 2.55 | .064 |
| | S17 - S20 | -0.87 | 1.00 |
| | S18 - S20 | -0.76 | 1.00 |
| | S19 - S20 | -3.00 | .016 |

**Table A13**
Dunn testing for season comparison of set piece group performance indicators, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Season Pair | $z$ | $p_{adj}$ |
|---|---|---|---|
| Lineouts Won | S17 - S18 | 1.22 | 1.00 |
| | S17 - S19 | 0.70 | 1.00 |
| | S18 - S19 | -0.40 | 1.00 |
| | S17 - S20 | -2.31 | .126 |
| | S18 - S20 | -3.39 | .004 |
| | S19 - S20 | -2.77 | .034 |
| Lineouts Lost | S17 - S18 | -0.01 | 1.00 |
| | S17 - S19 | -1.67 | .574 |
| | S18 - S19 | -1.65 | .589 |
| | S17 - S20 | -2.53 | .068 |
| | S18 - S20 | -2.52 | .071 |
| | S19 - S20 | -0.83 | 1.00 |
| Scrums Won | S17 - S18 | 2.60 | .056 |
| | S17 - S19 | 0.65 | 1.00 |
| | S18 - S19 | -1.71 | .529 |
| | S17 - S20 | 2.01 | .265 |
| | S18 - S20 | -0.29 | 1.00 |
| | S19 - S20 | 1.27 | 1.00 |
| Scrums Lost | S17 - S18 | 0.72 | 1.00 |
| | S17 - S19 | 1.77 | .460 |
| | S18 - S19 | 1.12 | 1.00 |
| | S17 - S20 | 0.24 | 1.00 |
| | S18 - S20 | -0.39 | 1.00 |
| | S19 - S20 | -1.38 | 1.00 |

**Table A14**
Dunn testing for season comparison of penalties and infringement group performance indicators, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Season Pair | $z$ | $p_{adj}$ |
|---|---|---|---|
| Penalties Conceded | S17 - S18 | 2.17 | 0.181 |
| | S17 - S19 | -0.34 | 1.00 |
| | S18 - S19 | -2.30 | .130 |
| | S17 - S20 | -4.44 | .000 |
| | S18 - S20 | -6.36 | .000 |
| | S19 - S20 | -3.79 | .001 |
| Free.Kicks | S17 - S18 | 1.74 | .488 |
| | S17 - S19 | 0.22 | 1.00 |
| | S18 - S19 | -1.36 | 1.00 |
| | S17 - S20 | -0.23 | 1.00 |
| | S18 - S20 | -1.78 | .454 |
| | S19 - S20 | -0.41 | 1.00 |
| Scrum Penalties | S17 - S18 | 0.76 | 1.00 |
| | S17 - S19 | 1.28 | 1.00 |
| | S18 - S19 | 0.59 | 1.00 |
| | S17 - S20 | 0.67 | 1.00 |
| | S18 - S20 | -0.01 | 1.00 |
| | S19 - S20 | -0.54 | 1.00 |
| Lineout Penalties | S17 - S18 | -1.47 | .857 |
| | S17 - S19 | -1.81 | .424 |
| | S18 - S19 | -0.48 | 1.00 |
| | S17 - S20 | -3.44 | .003 |
| | S18 - S20 | -2.14 | .193 |
| | S19 - S20 | -1.54 | .741 |
| Tackle/Ruck/Maul Penalties | S17 - S18 | 1.24 | 1.00 |
| | S17 - S19 | -0.16 | 1.00 |
| | S18 - S19 | -1.29 | 1.00 |
| | S17 - S20 | -5.52 | .000 |
| | S18 - S20 | -6.62 | .000 |
| | S19 - S20 | -4.94 | .000 |
| General Play Penalties | S17 - S18 | 3.46 | .003 |
| | S17 - S19 | 0.41 | 1.00 |
| | S18 - S19 | -2.71 | .040 |
| | S17 - S20 | -0.18 | 1.00 |
| | S18 - S20 | -3.24 | .007 |
| | S19 - S20 | -0.54 | 1.00 |
| Control Penalties | S17 - S18 | -0.68 | 1.00 |
| | S17 - S19 | -1.68 | .556 |
| | S18 - S19 | -1.07 | 1.00 |
| | S17 - S20 | -0.44 | 1.00 |
| | S18 - S20 | 0.15 | 1.00 |
| | S19 - S20 | 1.11 | 1.00 |

**Table A15**
Dunn testing for season comparison of card group performance indicators, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Season Pair | $z$ | $p_{adj}$ |
|---|---|---|---|
| Yellow Cards | S17 - S18 | -0.58 | 1.00 |
| | S17 - S19 | -2.78 | .033 |
| | S18 - S19 | -2.26 | .143 |
| | S17 - S20 | -4.26 | .000 |
| | S18 - S20 | -3.74 | .001 |
| | S19 - S20 | -1.41 | .945 |
| Red Cards | S17 - S18 | -0.77 | 1.00 |
| | S17 - S19 | -1.90 | .349 |
| | S18 - S19 | -1.20 | 1.00 |
| | S17 - S20 | -2.34 | .115 |
| | S18 - S20 | -1.66 | .582 |
| | S19 - S20 | -0.45 | 1.00 |

## A.5 Match Outcome Differences

**Table A16**

Summary of Mann Whitney U test statistic and $p_{adj}$ values for isolated variables and Wilcoxon Signed Rank Statistic and $p_{adj}$ Values for relative variables in season 2020/21. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Season | PI | Isolated Mann Whitney U Statistic Value | Isolated Mann Whitney $P_{adj}$ | Relative Wilcoxon Signed Rank Statistic Value | Relative Wilcoxon Signed Rank $P_{adj}$ |
|---|---|---|---|---|---|
| S20 | Carries | 4373.00 | 1.00 | 2120.50 | 1.00 |
| S20 | Metres Made | 3163.00 | .005 | 1365.50 | .022 |
| S20 | Defenders Beaten | 4294.50 | 1.00 | 1932.00 | 1.00 |
| S20 | Offloads | 4426.00 | 1.00 | 1684.50 | 1.00 |
| S20 | Passes | 5147.00 | 1.00 | 2666.50 | 1.00 |
| S20 | Tackle | 4758.50 | 1.00 | 2426.00 | 1.00 |
| S20 | Missed Tackle | 4921.50 | 1.00 | 2346.00 | 1.00 |
| S20 | Turnover Conceded | 5721.50 | .096 | 2675.00 | .032 |
| S20 | Kicks from Hand | 3318.00 | .021 | 733.00 | .000 |
| S20 | Clean Breaks | 3452.00 | .067 | 1338.00 | .110 |
| S20 | Turnovers Won | 3704.50 | .469 | 1159.00 | .203 |
| S20 | Lineouts Won | 4529.00 | 1.00 | 2092.00 | 1.00 |
| S20 | Lineouts Lost | 5335.00 | 1.00 | 1748.00 | 1.00 |
| S20 | Scrums Won | 4245.50 | 1.00 | 1653.50 | 1.00 |
| S20 | Scrums Lost | 4804.00 | 1.00 | 753.50 | 1.00 |
| S20 | Rucks Won | 4492.50 | 1.00 | 2312.50 | 1.00 |
| S20 | Rucks Lost | 5086.00 | 1.00 | 2076.00 | 1.00 |
| S20 | Penalties Conceded | 5160.50 | 1.00 | 2258.00 | 1.00 |
| S20 | Free Kicks | 4712.50 | 1.00 | 511.50 | 1.00 |
| S20 | Scrum Penalties | 5436.00 | .705 | 1951.00 | .268 |
| S20 | Lineout Penalties | 4752.50 | 1.00 | 668.00 | 1.00 |
| S20 | Tackle/Ruck/Maul Penalties | 4660.00 | 1.00 | 1899.50 | 1.00 |
| S20 | General Play Penalties | 4737.50 | 1.00 | 1247.00 | 1.00 |
| S20 | Control Penalties | 4953.00 | 1.00 | 1169.00 | 1.00 |
| S20 | Yellow Cards | 4905.50 | 1.00 | 741.00 | 1.00 |
| S20 | Red Cards | 4608.00 | 1.00 | 52.50 | 1.00 |

## A.6 Six Figure Summaries of Performance Indicators by Group.

**Table A17**

A table of minimum, 1st quartile, median, mean, 3rd quartile and maximum values for all performance indicators, for the isolated dataset for 2020/21 season.

| | Minimum | 1st Quartile | Median | Mean | 3rd Quartile | Maximum |
|---|---|---|---|---|---|---|
| Carries | 48.00 | 88.00 | 105.50 | 108.81 | 129.25 | 186.00 |
| Metres Made | 117.00 | 242.50 | 320.00 | 326.83 | 387.00 | 688.00 |
| Defenders Beaten | 2.00 | 11.75 | 16.00 | 16.97 | 21.00 | 44.00 |
| Offloads | 0.00 | 3.00 | 5.00 | 5.56 | 7.00 | 21.00 |
| Passes | 56.00 | 108.00 | 131.50 | 134.64 | 158.00 | 248.00 |
| Tackles | 50.00 | 102.00 | 128.50 | 131.16 | 156.50 | 241.00 |
| Missed Tackles | 2.00 | 11.75 | 16.00 | 16.97 | 21.00 | 44.00 |
| Turnovers Conceded | 4.00 | 10.00 | 12.00 | 12.00 | 14.00 | 23.00 |
| Kicks from Hand | 10.00 | 20.00 | 24.00 | 24.56 | 29.00 | 41.00 |
| Clean Breaks | 0.00 | 4.00 | 6.00 | 6.30 | 8.00 | 26.00 |
| Turnovers Won | 0.00 | 4.00 | 5.00 | 5.47 | 7.00 | 13.00 |
| Lineouts Won | 5.00 | 10.00 | 12.00 | 12.55 | 15.00 | 22.00 |
| Lineouts Lost | 0.00 | 1.00 | 2.00 | 1.94 | 3.00 | 6.00 |
| Scrums Won | 1.00 | 4.00 | 6.00 | 5.93 | 7.00 | 17.00 |
| Scrums Lost | 0.00 | 0.00 | 0.00 | 0.47 | 1.00 | 3.00 |
| Rucks Won | 37.00 | 68.00 | 81.00 | 84.98 | 102.00 | 148.00 |
| Rucks Lost | 0.00 | 2.00 | 3.00 | 3.25 | 4.00 | 12.00 |
| Penalties Conceded | 3.00 | 9.00 | 10.00 | 10.83 | 13.00 | 19.00 |
| Free Kicks | 0.00 | 0.00 | 0.00 | 0.64 | 1.00 | 3.00 |
| Scrum Penalties | 0.00 | 1.00 | 1.00 | 1.66 | 3.00 | 9.00 |
| Lineout Penalties | 0.00 | 0.00 | 0.00 | 0.47 | 1.00 | 4.00 |
| Tackle/Ruck/Maul Penalties | 1.00 | 4.00 | 6.00 | 5.76 | 7.00 | 11.00 |
| General Play Penalties | 0.00 | 1.00 | 2.00 | 1.92 | 3.00 | 6.00 |
| Control Penalties | 0.00 | 0.00 | 1.00 | 1.09 | 2.00 | 4.00 |
| Yellow Cards | 0.00 | 0.00 | 1.00 | 0.64 | 1.00 | 3.00 |
| Red Cards | 0.00 | 0.00 | 0.00 | 0.07 | 0.00 | 1.00 |

**Table A18**

A table of minimum, 1st quartile, median, mean, 3rd quartile and maximum values for all performance indicators, for the relative dataset for the 2020/21 season.

| | Minimum | 1st Quartile | Median | Mean | 3rd Quartile | Maximum |
|---|---|---|---|---|---|---|
| Carries | -117.00 | -29.00 | 0.00 | 0.00 | 29.00 | 117.00 |
| Metres Made | -504.00 | -96.00 | 0.00 | 0.00 | 96.00 | 504.00 |
| Defenders Beaten | -33.00 | -7.00 | 0.00 | 0.00 | 7.00 | 33.00 |
| Offloads | -19.00 | -3.00 | 0.00 | 0.00 | 3.00 | 19.00 |
| Passes | -132.00 | -33.50 | 0.00 | 0.00 | 33.50 | 132.00 |
| Tackles | -168.00 | -42.25 | 0.00 | 0.00 | 42.25 | 168.00 |
| Missed Tackles | -33.00 | -7.00 | 0.00 | 0.00 | 7.00 | 33.00 |
| Turnover Conceded | -13.00 | -3.00 | 0.00 | 0.00 | 3.00 | 13.00 |
| Kicks from Hand | -20.00 | -4.00 | 0.00 | 0.00 | 4.00 | 20.00 |
| Clean Breaks | -22.00 | -3.00 | 0.00 | 0.00 | 3.00 | 22.00 |
| Turnovers Won | -8.00 | -2.00 | 0.00 | 0.00 | 2.00 | 8.00 |
| Lineouts Won | -10.00 | -4.00 | 0.00 | 0.00 | 4.00 | 10.00 |
| Lineouts Lost | -5.00 | -1.00 | 0.00 | 0.00 | 1.00 | 5.00 |
| Scrums Won | -16.00 | -2.00 | 0.00 | 0.00 | 2.00 | 16.00 |
| Scrums Lost | -2.00 | -1.00 | 0.00 | 0.00 | 1.00 | 2.00 |
| Rucks Won | -99.00 | -27.25 | 0.00 | 0.00 | 27.25 | 99.00 |
| Rucks Lost | -8.00 | -2.00 | 0.00 | 0.00 | 2.00 | 8.00 |
| Penalties Conceded | -15.00 | -2.00 | 0.00 | 0.00 | 2.00 | 15.00 |
| Free Kicks | -3.00 | 0.00 | 0.00 | 0.00 | 0.00 | 3.00 |
| Scrum Penalty | -8.00 | -1.00 | 0.00 | 0.00 | 1.00 | 8.00 |
| Lineout Penalty | -4.00 | -1.00 | 0.00 | 0.00 | 1.00 | 4.00 |
| Tackle/Ruck/Maul Penalties | -7.00 | -2.00 | 0.00 | 0.00 | 2.00 | 7.00 |
| General Play Penalties | -4.00 | -1.00 | 0.00 | 0.00 | 1.00 | 4.00 |
| Control Penalties | -4.00 | -1.00 | 0.00 | 0.00 | 1.00 | 4.00 |
| Yellow Cards | -2.00 | -1.00 | 0.00 | 0.00 | 1.00 | 2.00 |
| Red Cards | -1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |

**This page has been left blank intentionally.**

## A.7 Correlation Matrices

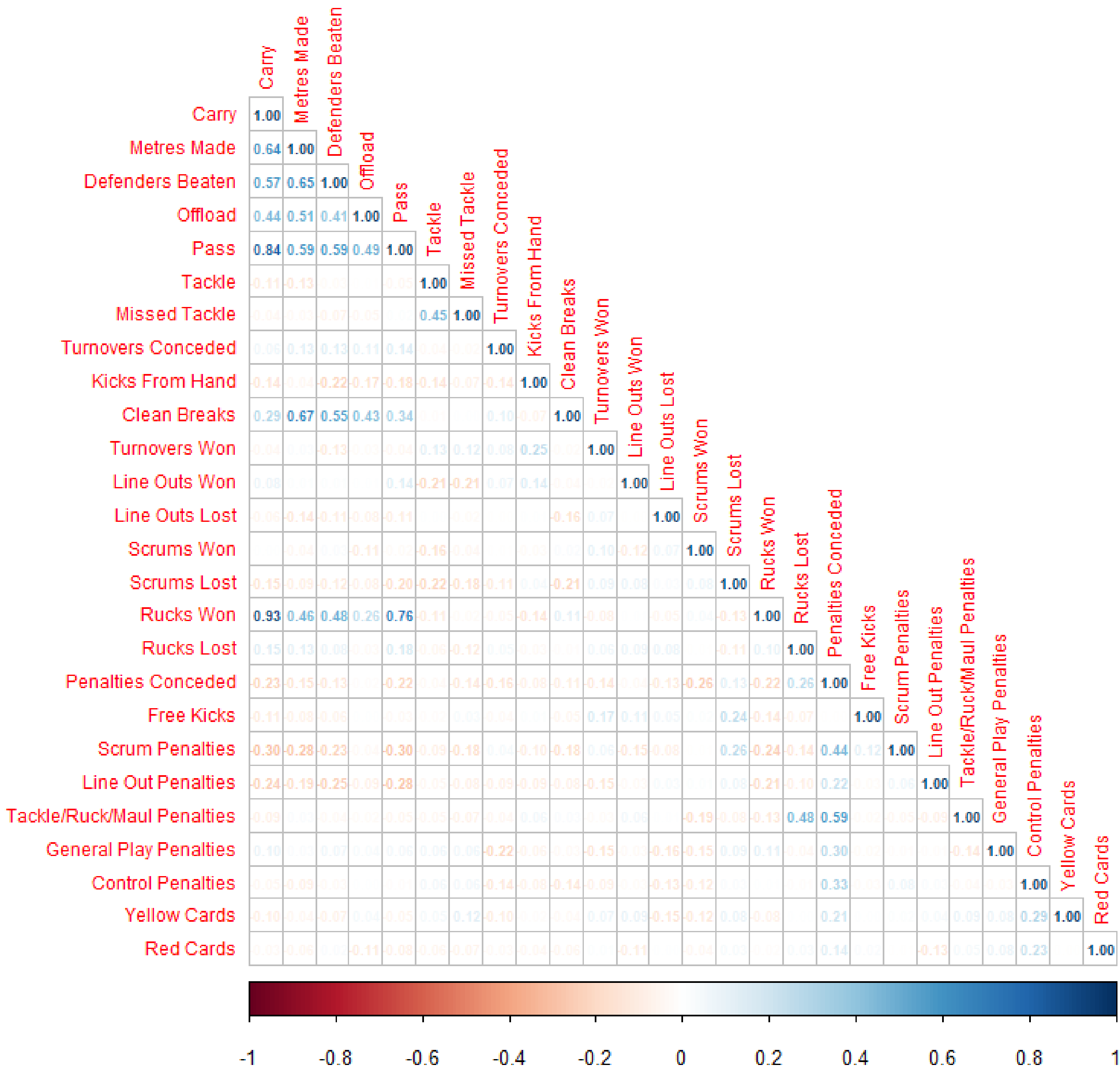



**Figure A3**
Lower triangular of correlation matrix for season 2020/21 isolated data. Red indicates a negative association and blue a positive association, with -1 representing a strong negative associations whereas +1 represents a strong positive association. The diagonal represents variables correlation with themselves so can be ignored in any interpretation.

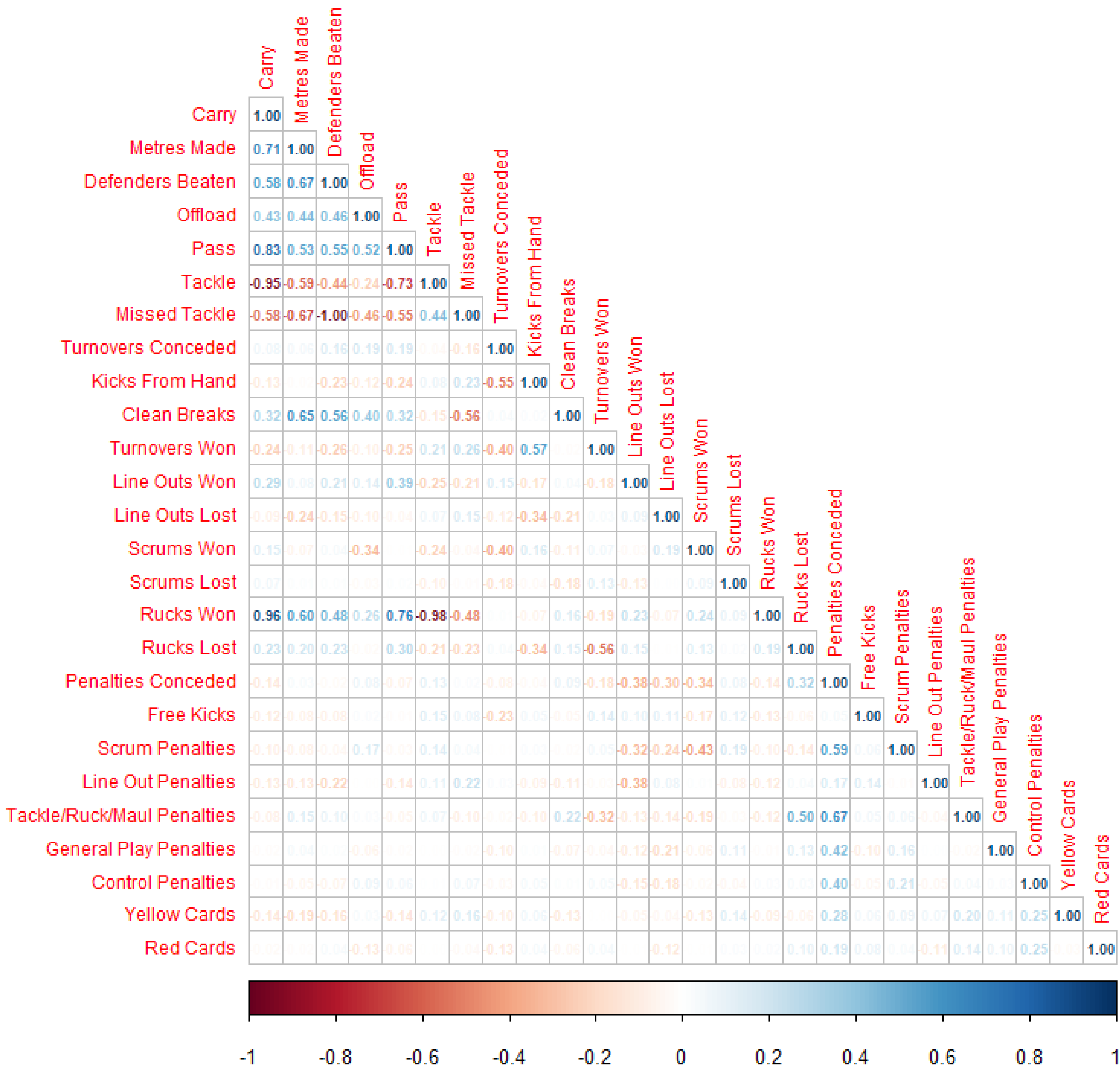


**Figure A4**
Lower triangular of correlation matrix for season 2020/21 relative data. Red indicates a negative association and blue a positive association, with -1 representing a strong negative associations whereas +1 represents a strong positive association. The diagonal represents variables correlation with themselves so can be ignored in any interpretation.

## A.8 Histograms and Skewness

**Table A19**
Breakdown of skewness for key performance indicators. This displays the skewness of all variables, moving from a non-zero value to a zero value when the data was transformed relatively.

| Variable | Isolated Skewness | Relative Skewness |
|---|---|---|
| Carries | 0.28 | 0 |
| Metres Made | 0.51 | 0 |
| Defenders Beaten | 0.89 | 0 |
| Offloads | 1.08 | 0 |
| Passes | 0.40 | 0 |
| Tackles | 0.39 | 0 |
| Missed Tackles | 0.89 | 0 |
| Turnovers Conceded | 0.29 | 0 |
| Kicks from Hand | 0.17 | 0 |
| Clean Breaks | 1.11 | 0 |
| Turnovers Won | 0.35 | 0 |
| Lineouts Won | 0.30 | 0 |
| Lineouts Lost | 0.81 | 0 |
| Scrums Won | 0.76 | 0 |
| Scrums Lost | 1.17 | 0 |
| Rucks Won | 0.38 | 0 |
| Rucks Lost | 0.59 | 0 |
| Penalties Conceded | 0.46 | 0 |
| Free Kicks | 0.92 | 0 |
| Scrum Penalties | 1.26 | 0 |
| Lineout Penalties | 1.69 | 0 |
| Tackle/Ruck/Maul Penalties | 0.16 | 0 |
| General Play Penalties | 0.77 | 0 |
| Control Penalties | 0.87 | 0 |
| Yellow Cards | 0.82 | 0 |
| Red Cards | 3.29 | 0 |
| Mean | 0.79 | 0 |

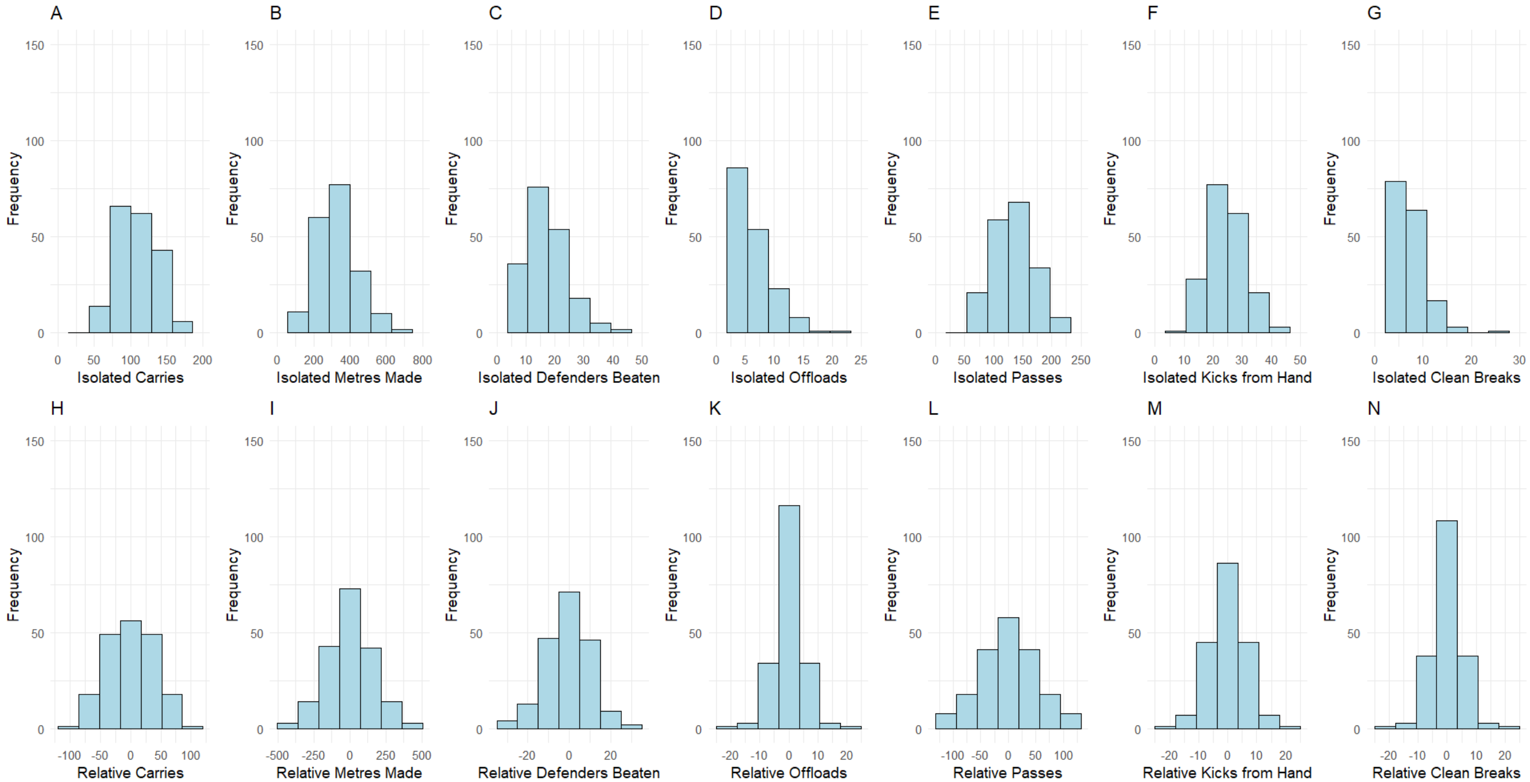



**Figure A5**

Histograms of Isolated and Relative Attack variables within the 2020/21 season. Plot A-G represent the histograms for Carries, Metres Made, Defenders Beaten, Offloads, Passes, Kicks from Hand and Clean Break as isolated values, respectively. Plots H-N represent the same variables in the same order, but with relative data values.

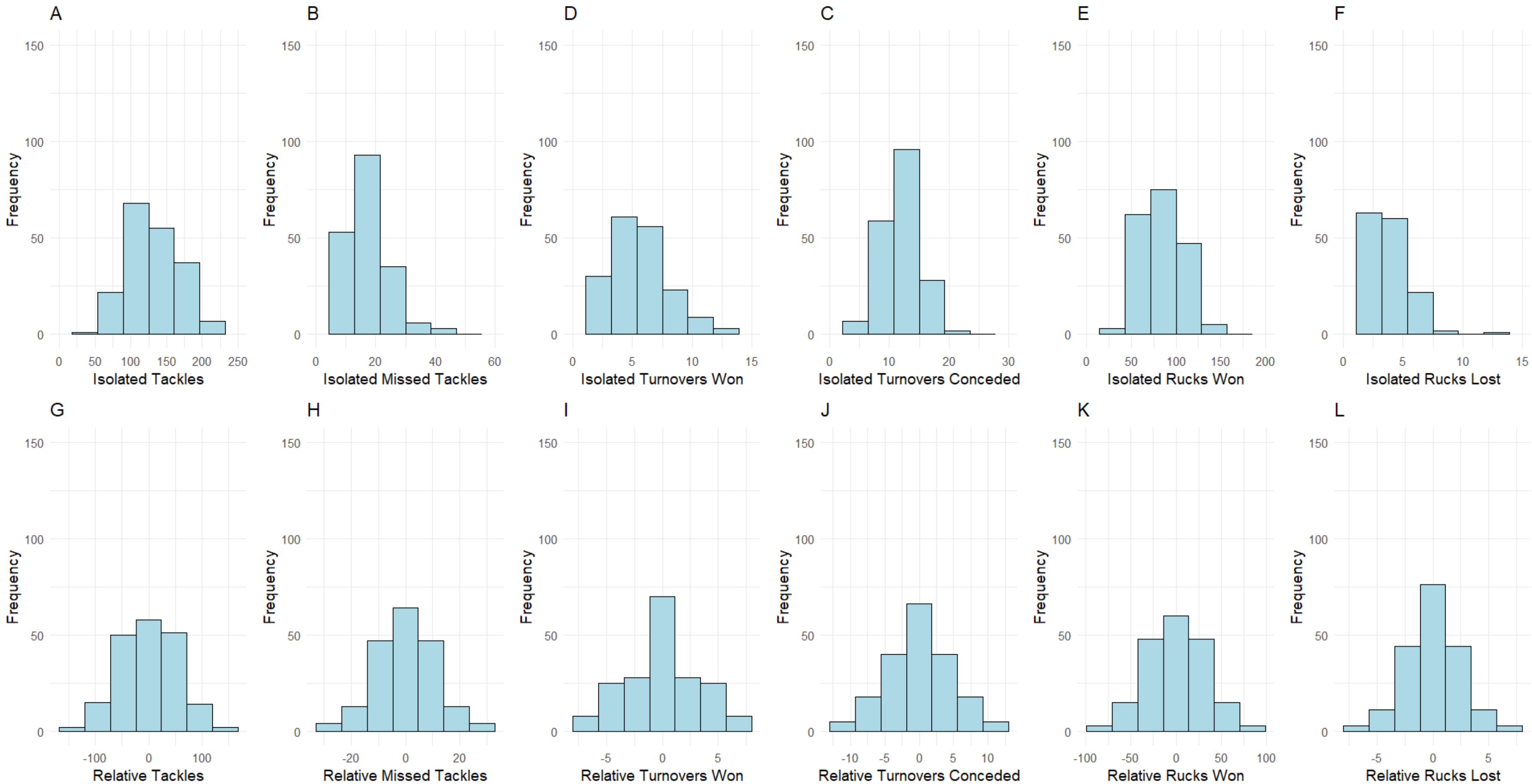



**Figure A6**

Histograms of Isolated and Relative Defence variables within the 2020/21 season. Plots A-F represent histograms of Tackles, Missed Tackles, Turnovers Won, Turnovers Conceded, Rucks Won and Ruck Lost respectively for the isolated data values, whereas plots G-K represent the same performance indicators in the same order, but with relative data values.

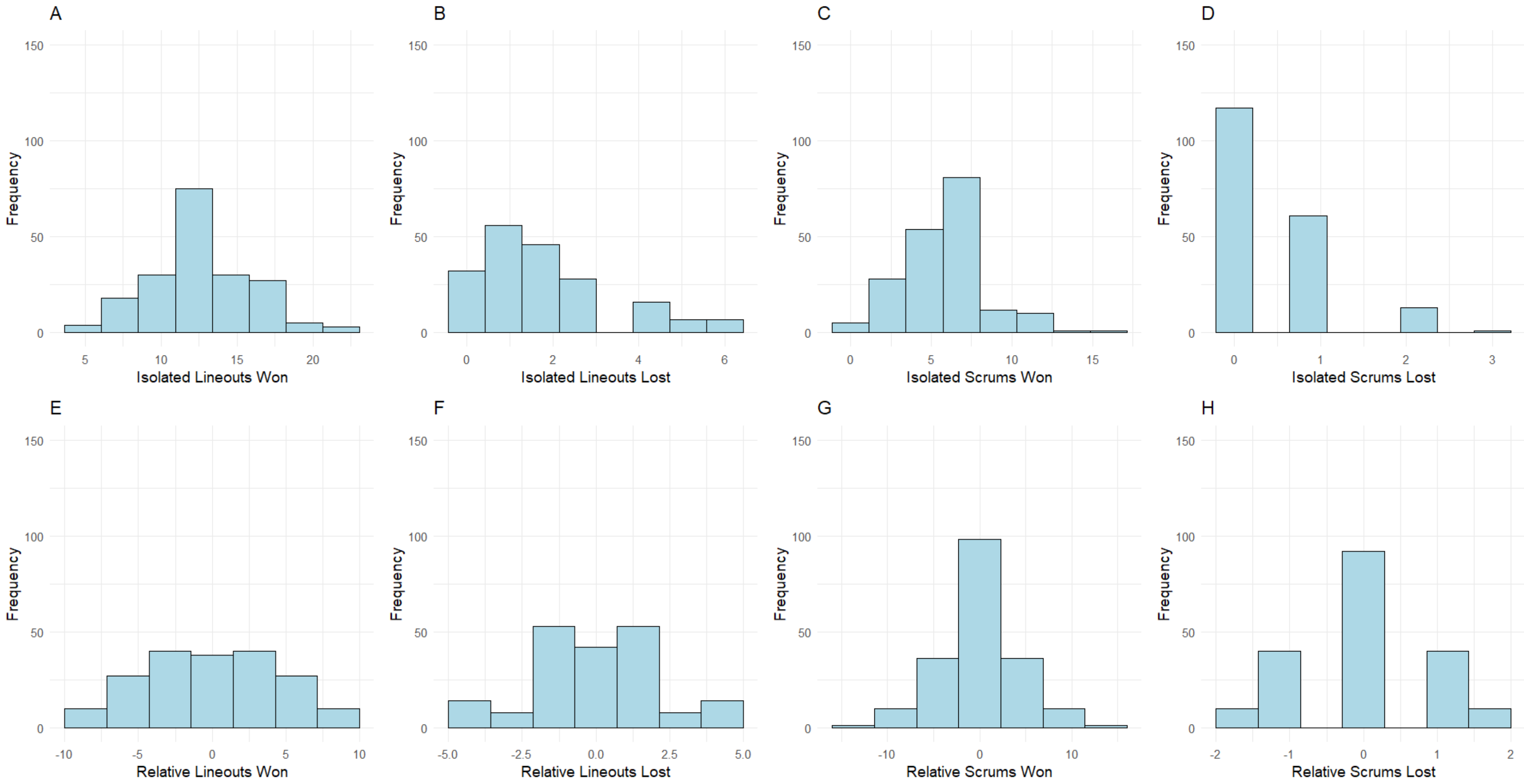



**Figure A7**
Histograms of Isolated and Relative Set Piece variables within the 2020/21 season. Plots A-D represent histograms of Lineouts Won Lineouts Lost, Scrums Won and Scrums Lost respectively for the isolated data values, whereas plots E-H represent the same performance indicators in the same order, but with relative data values.

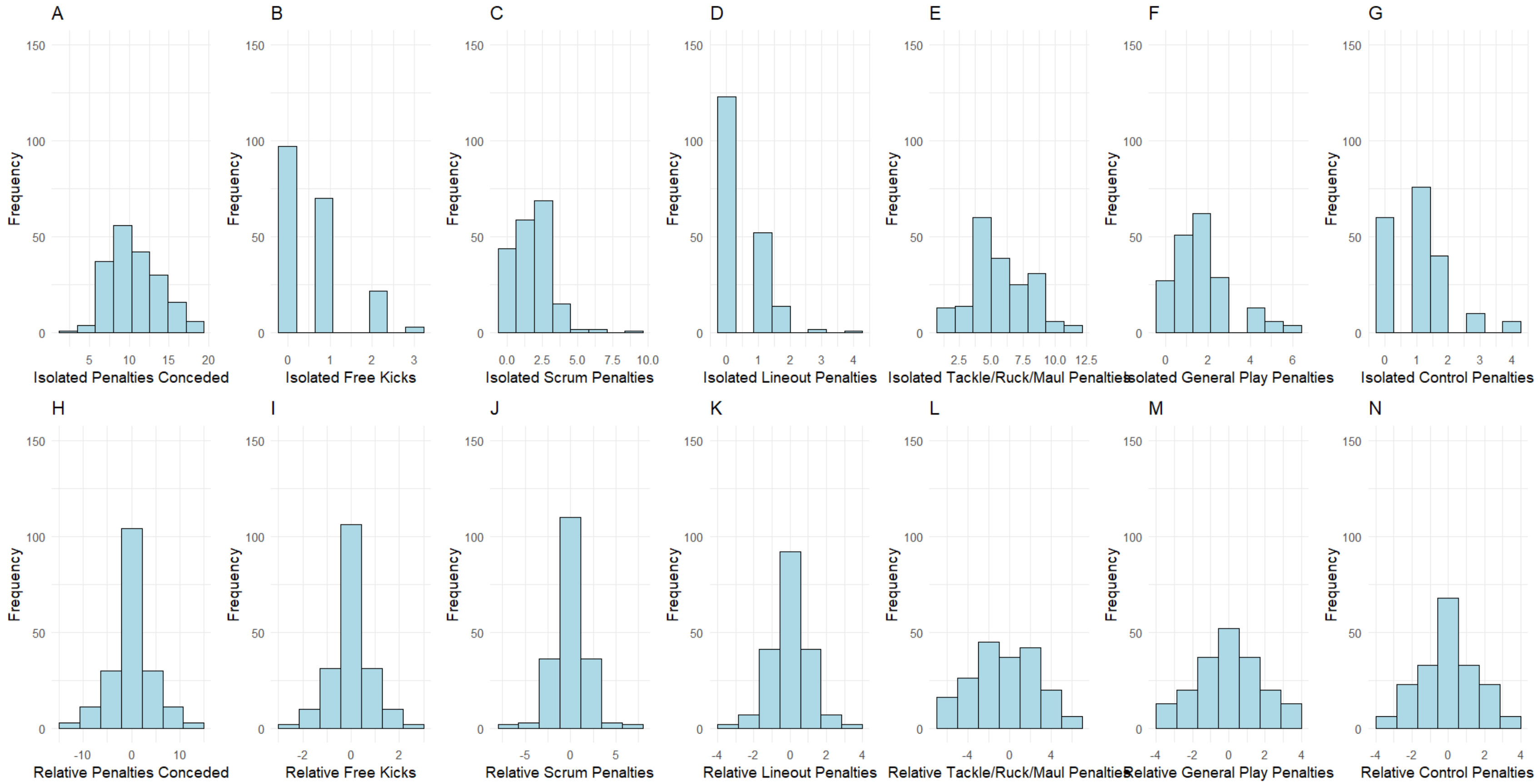



**Figure A8**
Histograms of Isolated and Relative Penalties and Infringement variables within the 2020/21 season. Plots A-G represent histograms of Penalties Conceded, Free Kicks, Scrum Penalties, Lineout Penalties, Tackle/Ruck/Maul Penalties, General Play Penalties and Control Penalties respectively for the isolated data values, whereas plots H-N represent the same performance indicators in the same order, but with relative data values.

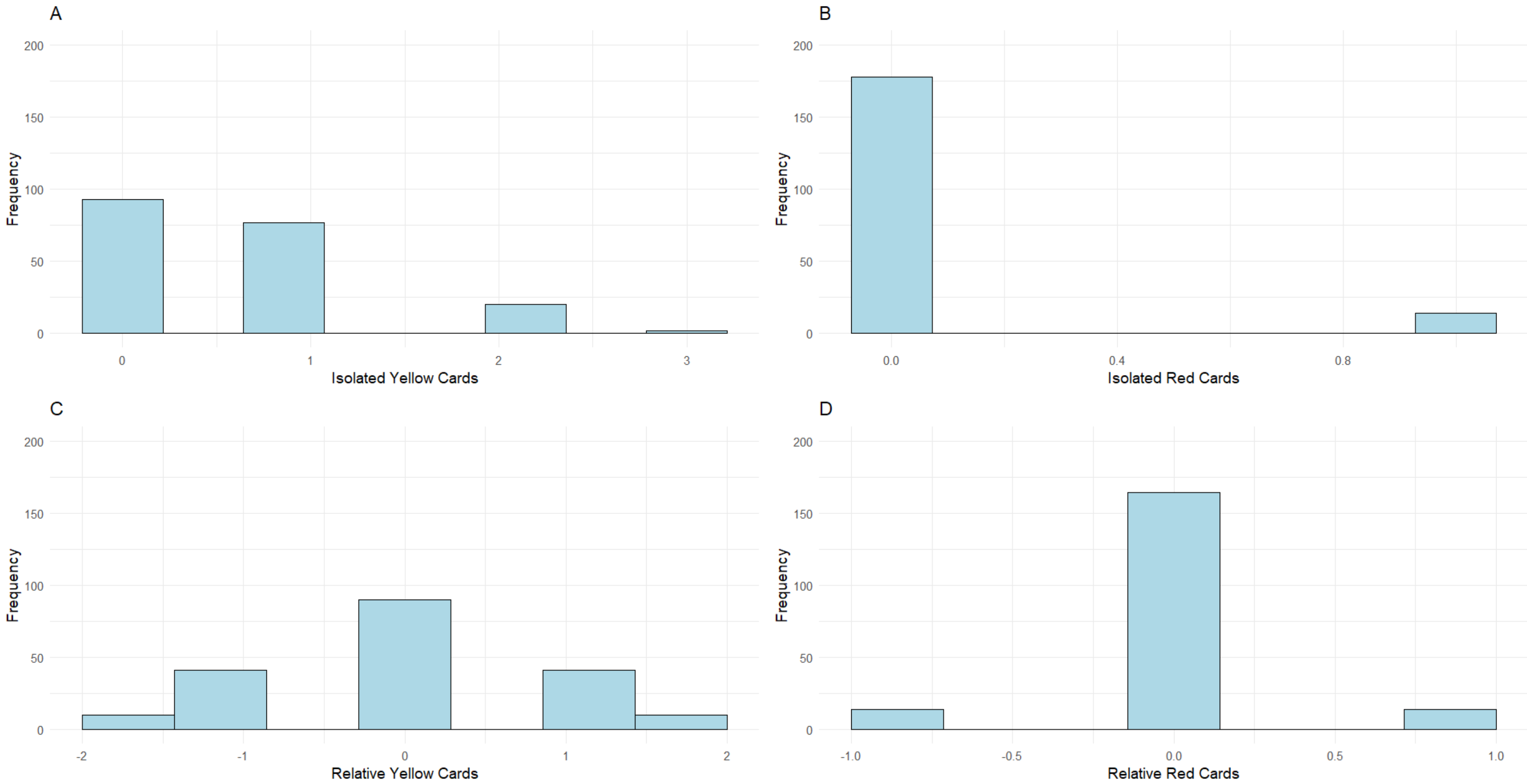



**Figure A9**
Histograms of Yellow and Red Cards within the 2020/21 season. Plots A-B represent histograms of Yellow and Red Cards respectively for the isolated data values, whereas plots C-D represent the same performance indicators in the same order, but with relative data values.

## A.9 Box plots

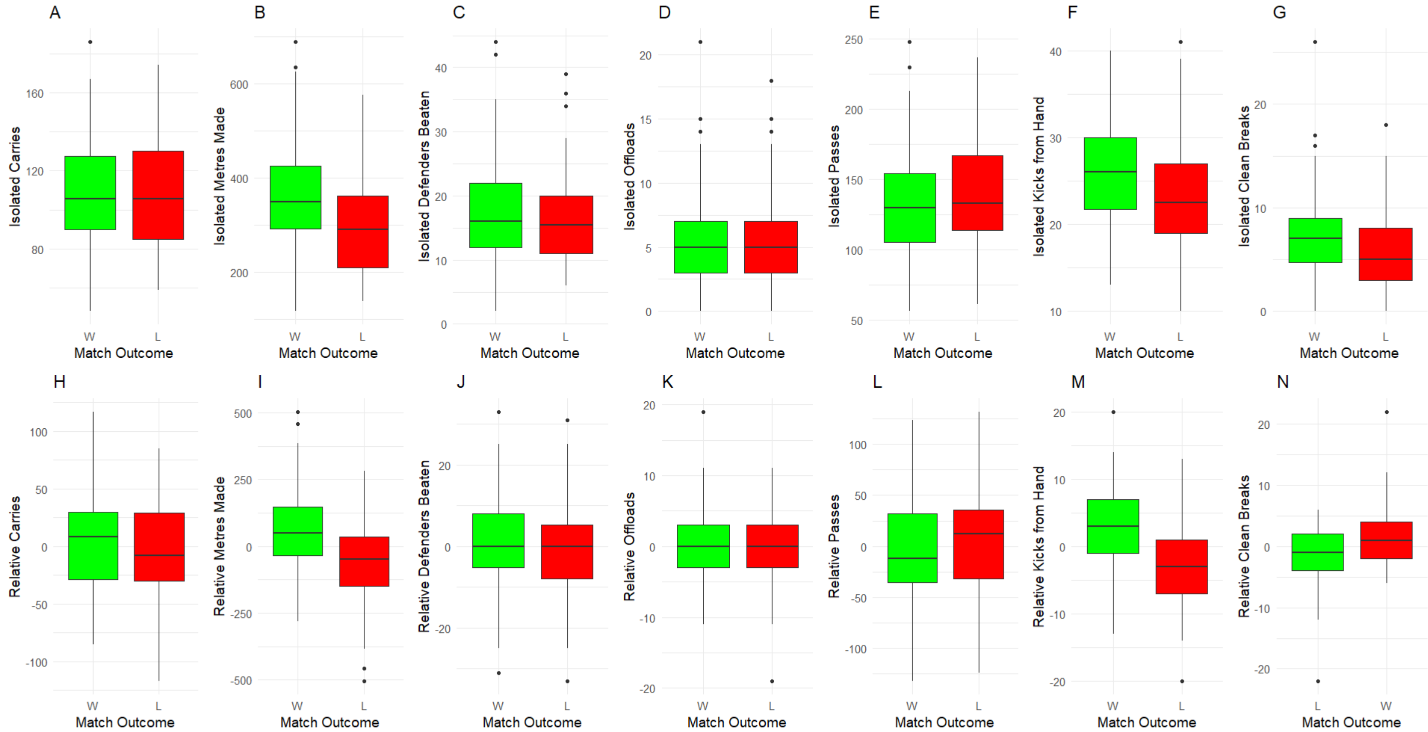



**Figure A10**
Box plots of Isolated and Relative Attack variables within the 2020/21 season, split by wins and losses marked ″W″ and ″L″ respectively. Plot A-G represent the box plots for Carries, Metres Made, Defenders Beaten, Offloads, Passes, Kicks from Hand and Clean Break as isolated values, respectively. Plots H-N represent the same performance indicators in the same order, but with relative data values.

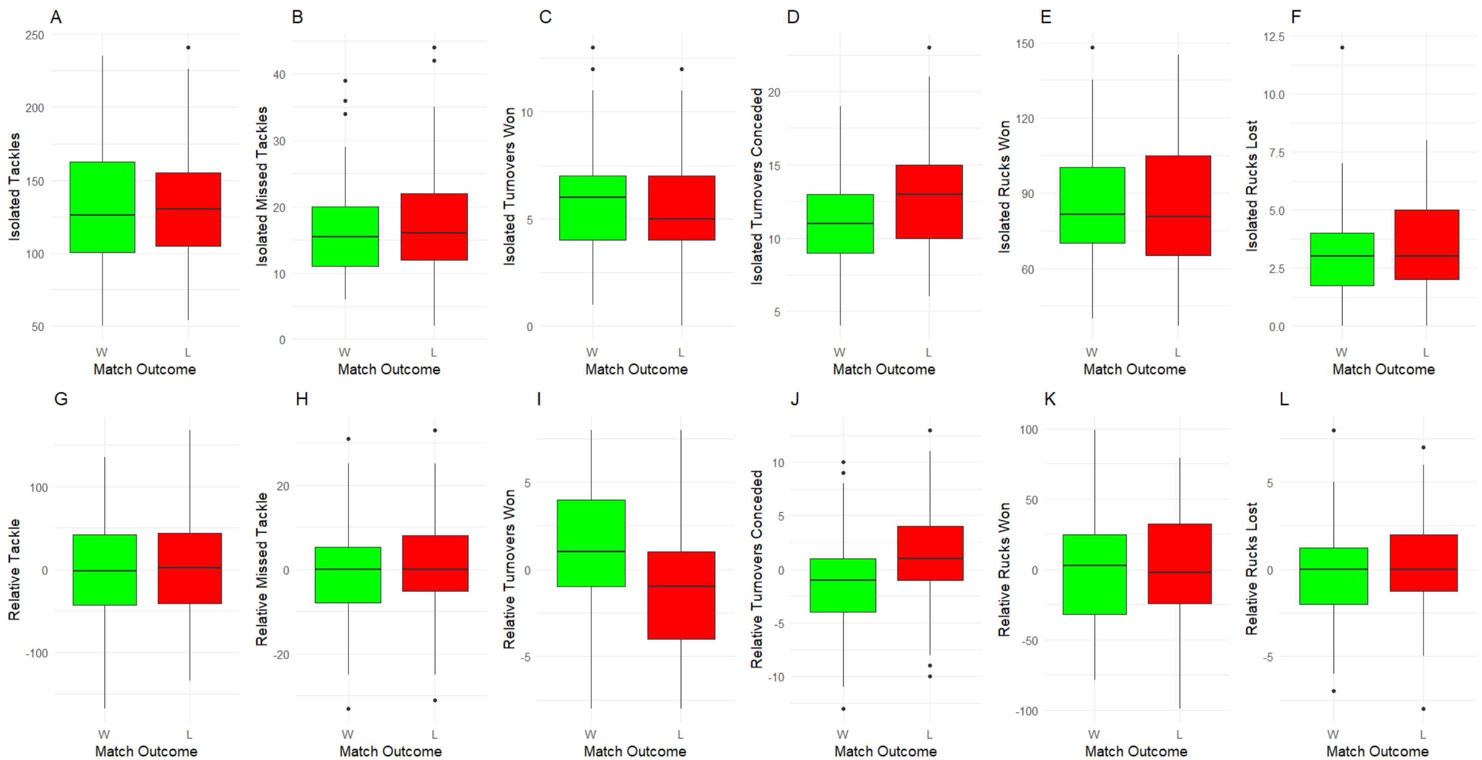



**Figure A11**
Box plots of Isolated and Relative Defence variables within the 2020/21 season, split by wins and losses marked ″W″ and ″L″ respectively. The black solid line represents the median value, whereas the colour box represents the range from the upper to lower quartiles. Plots A-F represent box- lots of Tackles, Missed Tackles, Turnovers Won, Turnovers Conceded, Rucks Won and Ruck Lost respectively for the isolated data values, whereas plots G-K represent the same performance indicators in the same order, but with relative data values.

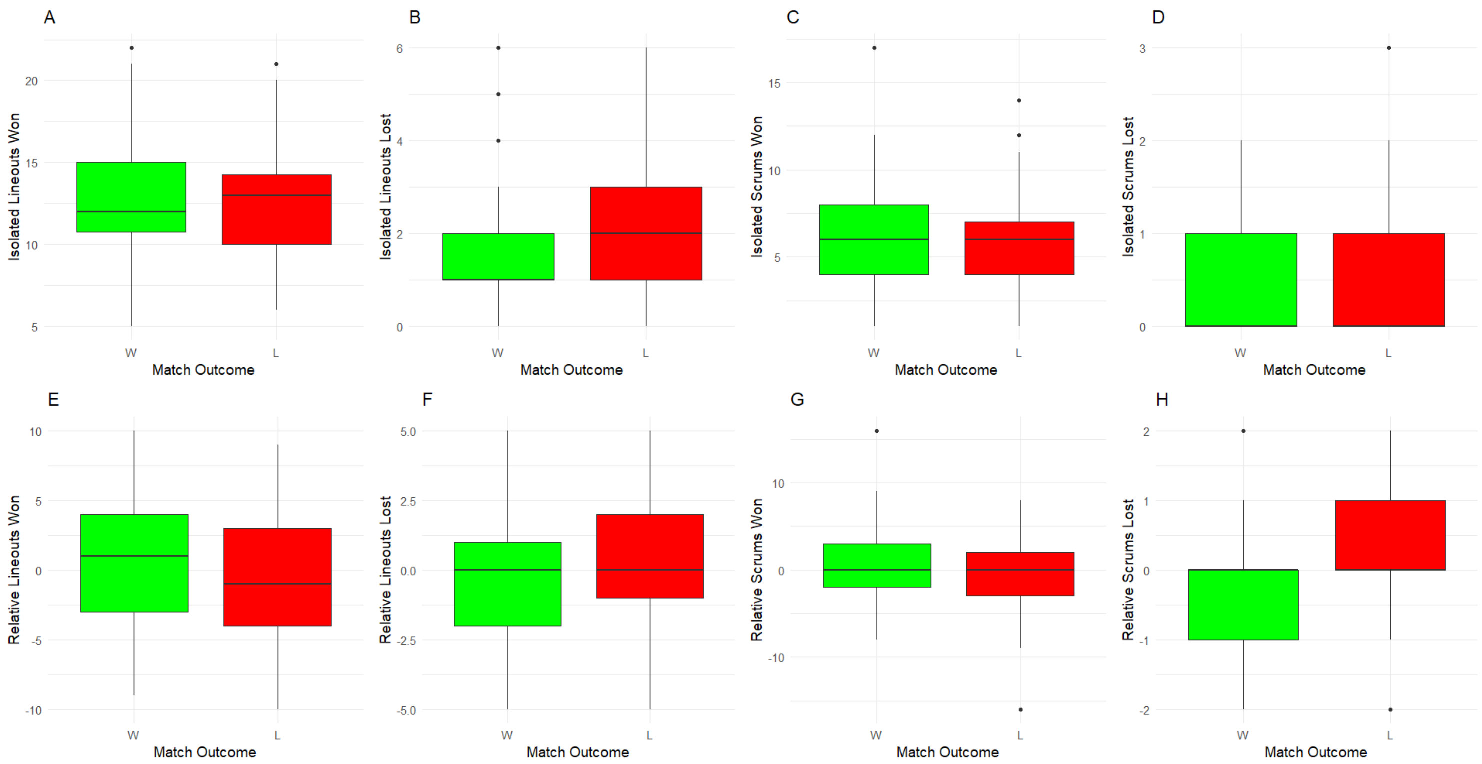



**Figure A12**
Box plots of Isolated and Relative Set Piece variables within the 2020/21 season, split by wins and losses marked "W" and "L" respectively. The black solid line represents the median value, whereas the colour box represents the range from the upper to lower quartiles. Plots A-D represent box plots of Lineouts Won Lineouts Lost, Scrums Won and Scrums Lost respectively for the isolated data values, whereas plots E-H represent the same performance indicators in the same order, but with relative data values.

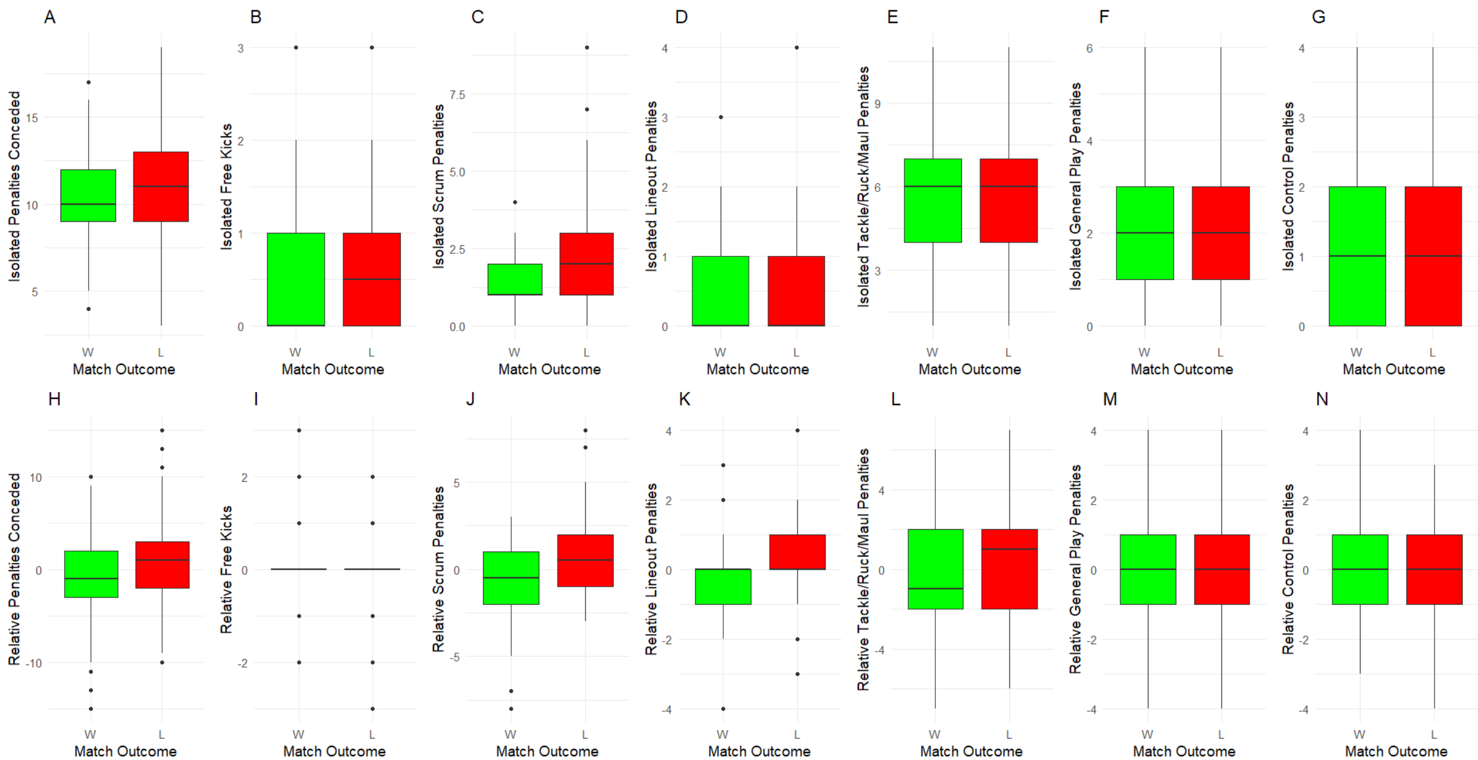



**Figure A13**

Box plots of Isolated and Relative Penalties and Infringement variables within the 2020/21 season, split by wins and losses marked ″W″ and ″L″ respectively. Plots A-G represent box plots of Penalties Conceded, Free Kicks, Scrum Penalties, Lineout Penalties, Tackle/Ruck/Maul Penalties, General Play Penalties and Control Penalties respectively for the isolated data values, whereas plots H-N represent the same performance indicators in the same order, but with relative data values.

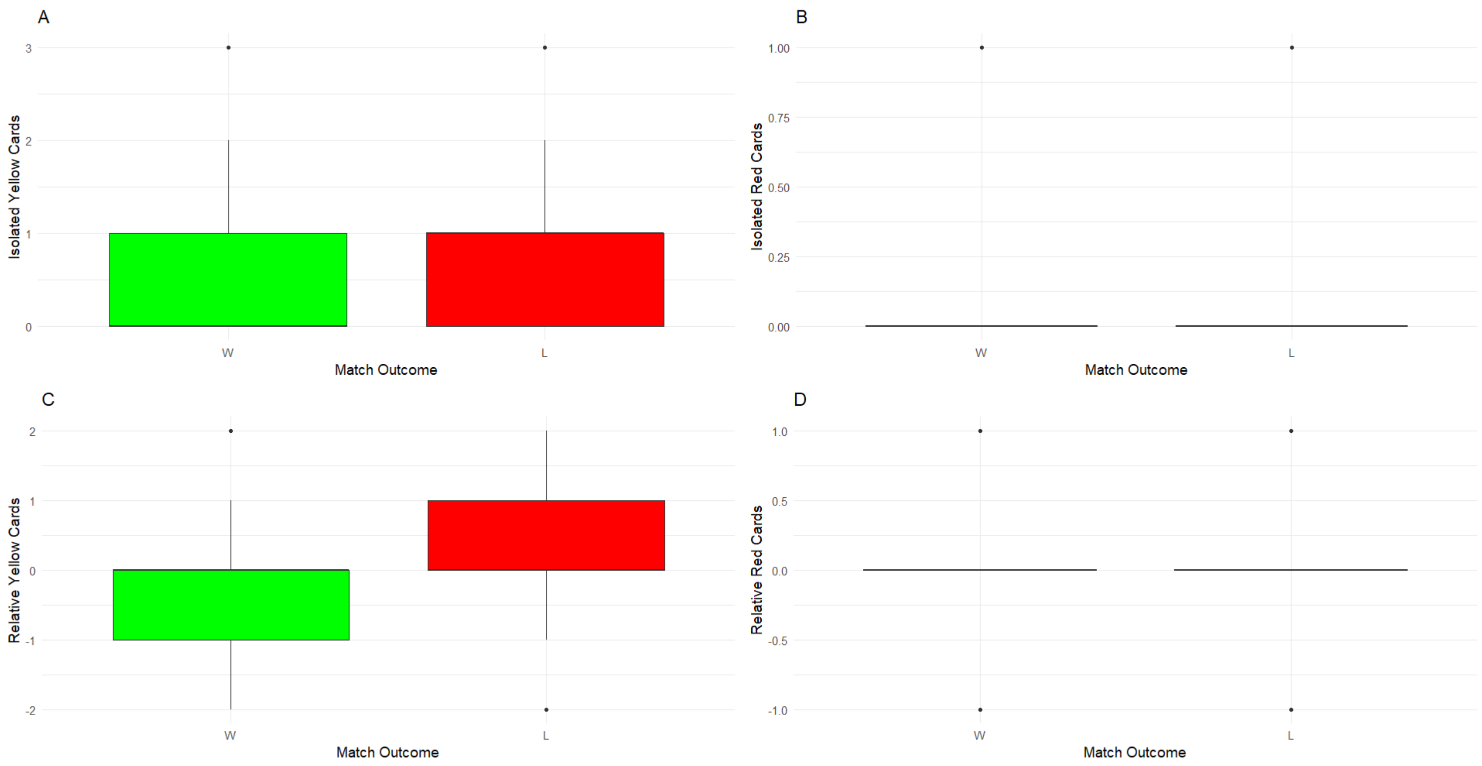



**Figure A14**
Box plots of Yellow and Red Cards within the 2020/21 season, split by wins and losses marked ″W″ and ″L″ respectively. Plots A-B represent box plots of Yellow and Red Cards respectively for the isolated data values, whereas plots C-D represent the same performance indicators in the same order, but with relative data values.

## A.10 Random Forest Plots

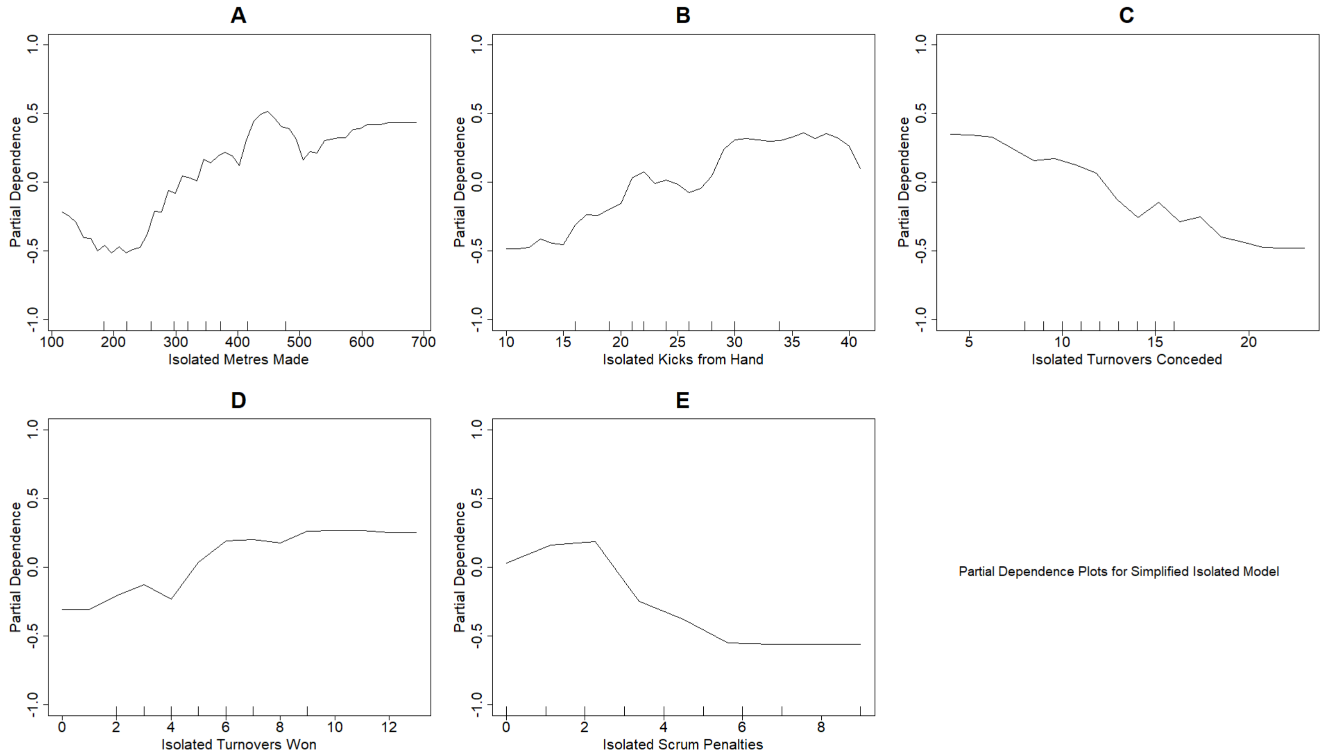



**Figure A15**
Partial dependence plots for significant variables (based on Mean Decrease Accuracy values) based on the simplified isolated model. The plots show the partial dependence of metres made (plot A), kicks from hand (plot B), turnovers conceded (plot C), turnovers won (plot D) and scrum penalties (plot E).

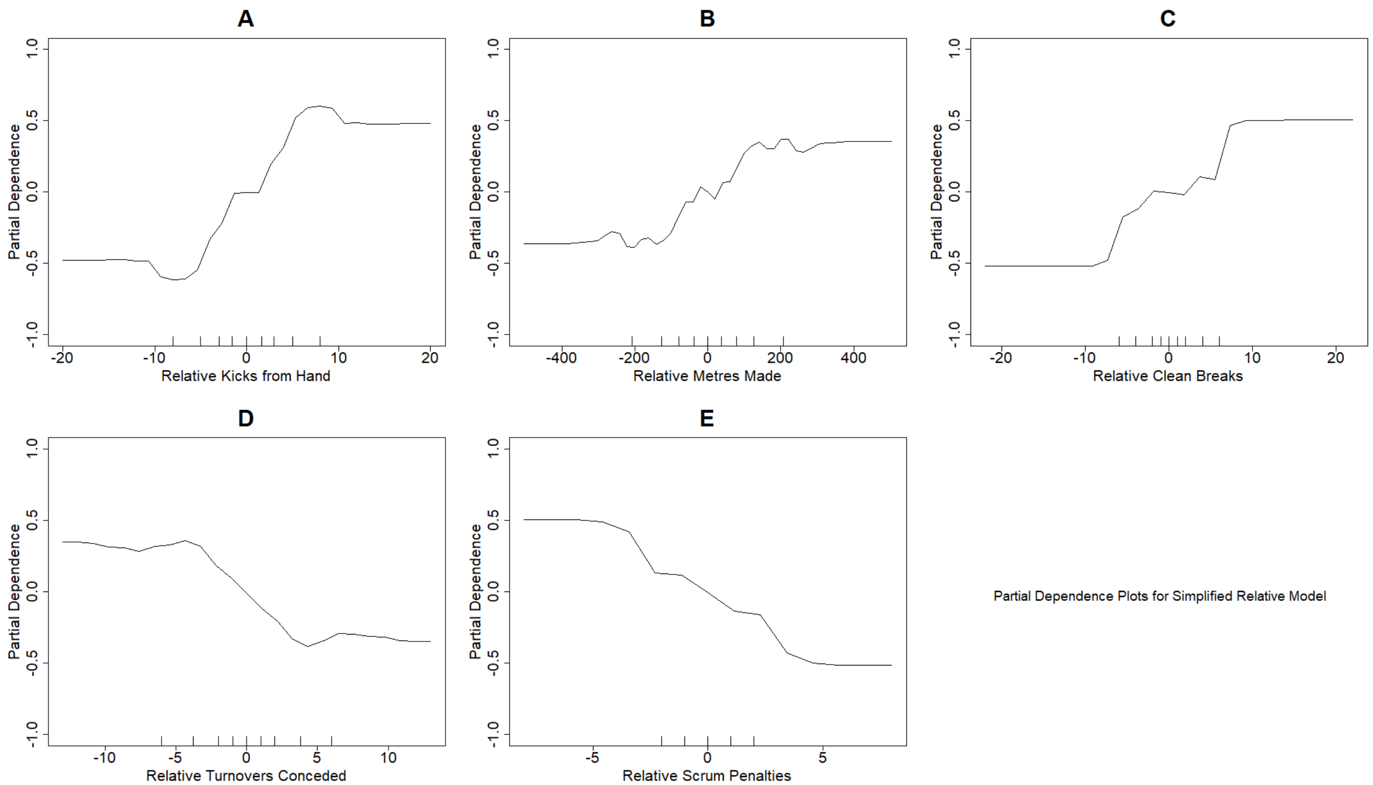



**Figure A16**

Partial dependence plots for significant variables (based on Mean Decrease Accuracy values) based on the simplified relative model. The plots show the partial dependence of relative kicks from hand (plot A), relative metres made (plot B), relative clean breaks (plot C), relative turnovers conceded (plot D) and relative scrum penalties (plot E).

**This page has been left blank intentionally.**

# B Appendix B

## B.1 Ethical Approval Letter

**LEAD APPLICANT NAME:** Georgia Scott
**DISCIPLINE/DEPARTMENT:** SPEX
**PROJECT TITLE:** The application of advanced data analytics to quantify load monitoring and performance, in professional rugby union.
**APPLICATION REFFERENCE NUMBER:** Georgia_Scott_27-10-22

Swansea University
Prifysgol Abertawe

**Date of review board:** November
**Committee members in attendance:** Chelsea Starbuck

**Date:** Monday 5th December 2022

Dear Georgia,

Thank you for your recent ethics application.

This decision letter is to inform you that the ethics application for the above titled project has been reviewed and approved. The ethical approval number for this application is GS_27-10-22, approved from 05/12/22– end of approval 31/07/24.

This letter is for Swansea University, College of Engineering Research Ethics and Governance approval only. Local Health and Safety, in addition to appropriate risk assessment guidelines are required separate to this approval, unless otherwise stated herein, and must be adhered to.

Associated researchers must not deviate from the approved protocol or extend beyond the approval end date. Any desired deviations or approval date extensions are subject to the ethical approval amendment process. Upon completion of the approved project researchers responsible for this application must submit a final (short) statement to the ethical committee stating the completion of the project, unless a time extension is being requested through the amendment process.

Any significant un-anticipated adverse effects/events (i.e. not those predicted and stated in section 8 of the ethics application form) must be reported to the Ethics committee upon researcher realisation (email: coe-researchethics@swansea.ac.uk; with the subject title including the study approval number followed by "Adverse Effects/Events").

If you have any further questions relating to your application, please contact: coe-researchethics@swansea.ac.uk.

Please keep note of your approval number for future reference and correspondence relating to this application.

Best of luck with your research.

Warm regards,

Aynsley Fagan

**(on behalf of the College of Engineering Research Ethics and Governance Chair)**

---

**College of Engineering Ethics and Governance Committee Administrator**
**College of Engineering | Y Coleg Peirianneg**
**Swansea University | Prifysgol Abertawe**
**Fabian Way | Ffordd Fabian Crymlyn Burrows**
**Swansea | Abertawe**
**Wales | Cymru**
**SA1 8EN**

**Email:** coe-researchethics@swansea.ac.uk.

**Figure B1**
Approval letter confirming ethical approval for experimental studies within Chapters 4,5 and 6.

## B.2 Dunn Testing

**Table B1**
Dunn testing for outcome comparison of total kicks, reference team kicks and relative kicks, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Kick Type | Outcome Pair | $z$ | $p_{adj}$ |
|---|---|---|---|
| Total Kicks | Negative - Positive | 1.60 | .546 |
| | Negative - Neutral | 1.34 | .330 |
| | Neutral - Positive | -0.21 | 1.00 |
| Reference Team Kicks | Negative - Positive | -2.17 | .089 |
| | Negative - Neutral | -12.93 | .000 |
| | Neutral - Positive | 11.56 | .000 |
| Relative Kicks | Negative - Positive | -4.34 | .000 |
| | Negative - Neutral | -18.00 | .000 |
| | Neutral - Positive | 14.59 | .000 |

**Table B2**
Dunn testing for outcome comparison by kick type of relative kick values, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Kick Type | Outcome Pair | $z$ | $p_{adj}$ |
|---|---|---|---|
| Bomb | Negative - Positive | -1.91 | .170 |
| | Negative - Neutral | -1.04 | .894 |
| | Neutral - Positive | -0.51 | 1.00 |
| Box | Negative - Positive | -1.81 | .212 |
| | Negative - Neutral | -10.94 | .000 |
| | Neutral - Positive | 9.53 | .000 |
| Chip | Negative - Positive | -0.83 | 1.00 |
| | Negative - Neutral | 2.00 | .138 |
| | Neutral - Positive | -3.05 | .007 |
| Cross Pitch | Negative - Positive | -2.24 | .075 |
| | Negative - Neutral | -2.11 | .104 |
| | Neutral - Positive | 0.34 | 1.00 |
| Low | Negative - Positive | -2.48 | .040 |
| | Negative - Neutral | 0.36 | 1.00 |
| | Neutral - Positive | -3.29 | .003 |
| Territorial | Negative - Positive | -4.05 | .000 |
| | Negative - Neutral | 1.61 | .323 |
| | Neutral - Positive | -5.95 | .000 |

**Table B3**
Dunn testing for detailed outcome comparison of relative kick values, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Detailed Outcome Pair | $z$ | $p_{adj}$ |
|---|---|---|
| Neutral Kick Out of Play - Neutral Other | 0.80 | 1.00 |
| Neutral Kick out of Play - Penalty Conceded | 17.34 | .000 |
| Neutral Other - Penalty Conceded | 11.65 | .000 |
| Neutral Kick Out of Play - Penalty Won | 16.15 | .000 |
| Neutral Other - Penalty Won | 10.19 | .000 |
| Penalty Conceded - Penalty Won | -2.36 | .515 |
| Neutral Kick Out of Play - Try Conceded | 5.51 | .000 |
| Neutral Other - Try Conceded | 4.39 | .000 |
| Penalty Conceded - Try Conceded | -3.64 | .007 |
| Penalty Won - Try Conceded | -2.32 | .570 |
| Neutral Kick Out of Play - Try Won | 3.01 | .073 |
| Neutral Other - Try Won | 2.13 | .922 |
| Penalty Conceded - Try Won | -6.42 | .000 |
| Penalty Won - Try Won | -5.11 | .000 |
| Try Conceded - Try Won | -2.01 | 1.00 |
| Neutral Kick Out of Play - Possession Conceded | 8.01 | .000 |
| Neutral Other - Possession Conceded | 4.78 | .000 |
| Penalty Conceded - Possession Conceded | -8.39 | .000 |
| Penalty Won - Possession Conceded | -6.52 | .000 |
| Try Conceded - Possession Conceded | -1.38 | 1.00 |
| Try Won - Possession Conceded | 1.20 | 1.00 |
| Neutral Kick Out of Play - Possession Won | 8.98 | .000 |
| Neutral Other - Possession Won | 5.68 | .000 |
| Penalty Conceded - Possession Won | -6.87 | .000 |
| Penalty Won - Possession Won | -4.96 | .000 |
| Try Conceded - Possession Won | -0.62 | 1.00 |
| Try Won - Possession Won | 1.96 | 1.00 |
| Possession Conceded - Possession Won | 1.24 | 1.00 |

# C Appendix C

## C.1 Mann Whitney Test Results

**Table C1**
Mann Whitney hypothesis testing comparing outcome score from different kick types between winning and losing teams. Single kick sequences were tested only, to maintain independence of observations.

| Zone | Winners Score | Losers Score | U Statistic | $p_{adj}$ |
|---|---|---|---|---|
| Red | 0.83 | 0.52 | 1716 | .030 |
| Silver | 0.31 | 0.15 | 5276 | .120 |
| Gold | 0.18 | 0.21 | 19723 | 1.00 |
| Blue | 0.13 | 0.04 | 25327 | 1.00 |
| Green | 0.05 | 0.02 | 147696 | 1.00 |

**Table C2**
Mann Whitney hypothesis testing comparing outcome score from kicks in different zones between winning and losing teams. Single kick sequences were tested only, to maintain independence of observations.

| Zone | Winners Score | Losers Score | U Statistic | $p_{adj}$ |
|---|---|---|---|---|
| Bomb | 0.13 | -0.15 | 1038 | .259 |
| Box | 0.11 | 0.08 | 65162 | 1.00 |
| Chip | 0.16 | 0.50 | 990 | 1.00 |
| Cross Pitch | 0.77 | 0.30 | 673 | .798 |
| Low | 0.36 | 0.33 | 7792 | .504 |
| Territorial | 0.30 | 0.30 | 17273 | .924 |
| Touch Kick | -0.03 | -0.09 | 53243 | 1.00 |

# D Appendix D

## D.1 Additional Distance and Time Plots

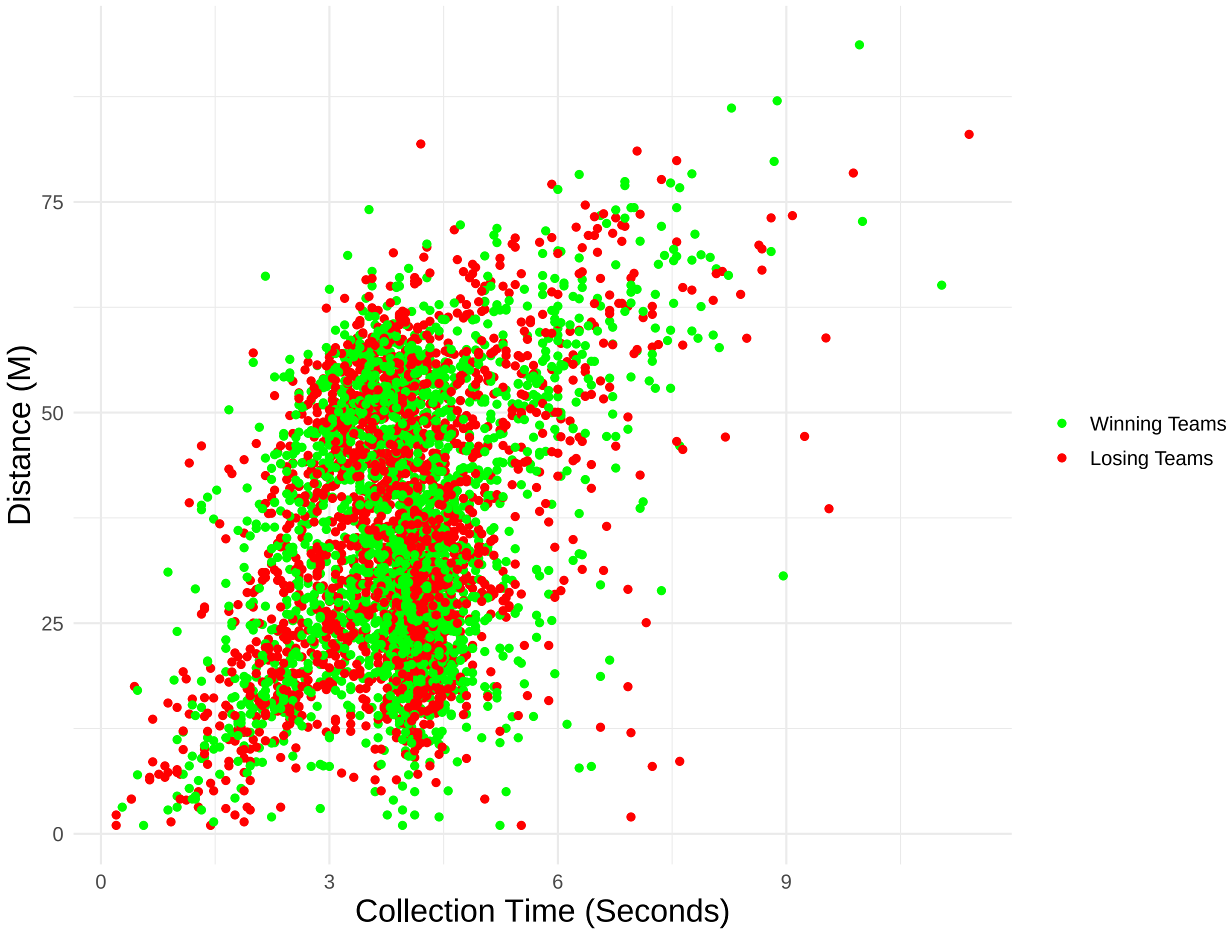



**Figure D1**
Distance-Time scatter plot of kicks separated by kick outcome. Distance (m) is represented by the $y$-axis and collection time (s) is represented by the $x$-axis with colour indicating whether the kick was made by a winning or losing team.

## D.2 Distance and Time Groups

**Table D1**
Table of frequency (n) of zone kicks in each distance range.

| | | Kick Distance | | | |
|---|---|---|---|---|---|
| | | 0-15 m | 15-25 m | 25-35 m | 35 m+ |
| Kick Zone | Red | 48 | 29 | 13 | 16 |
| | Silver | 51 | 83 | 96 | 48 |
| | Gold | 109 | 326 | 360 | 363 |
| | Blue | 97 | 368 | 421 | 947 |
| | Green | 31 | 97 | 158 | 783 |

**Table D2**
Table of frequency (n) of zone kicks in each collection time range.

| | | Kick Collection Time | | |
|---|---|---|---|---|
| | | 0-3 s | 3-5 s | 5 s+ |
| Kick Zone | Red | 84 | 21 | 1 |
| | Silver | 150 | 113 | 14 |
| | Gold | 247 | 769 | 142 |
| | Blue | 212 | 1374 | 247 |
| | Green | 105 | 810 | 154 |

**Table D3**
Table of frequency (n) of kick types in each distance range.

| | | Kick Distance | | | |
|---|---|---|---|---|---|
| | | 0-15 m | 15-25 m | 25-35 m | 35 m+ |
| Kick Type | Bomb | 10 | 106 | 157 | 52 |
| | Box | 130 | 466 | 485 | 244 |
| | Chip | 40 | 97 | 67 | 19 |
| | Cross Pitch | 0 | 7 | 30 | 56 |
| | Low | 122 | 123 | 116 | 62 |
| | Territorial | 33 | 104 | 193 | 1663 |
| | Touch Kick | 0 | 0 | 0 | 61 |

**Table D4**
Table of frequency (n) of kick types in each collection time range.

| | | Kick Collection Time | | |
|---|---|---|---|---|
| | | 0-3 s | 3-5 s | 5 s+ |
| Kick Type | Bomb | 10 | 279 | 36 |
| | Box | 73 | 1167 | 85 |
| | Chip | 134 | 74 | 15 |
| | Cross Pitch | 71 | 20 | 2 |
| | Low | 241 | 152 | 30 |
| | Territorial | 257 | 1356 | 380 |
| | Touch Kick | 12 | 39 | 10 |

**Table D5**
Table of frequency (n) of kick outcome in each distance range.

| | | Kick Distance | | | |
|---|---|---|---|---|---|
| | | 0-15 m | 15-25 m | 25-35 m | 35 m+ |
| Kick Outcome | Caught Full | 59 | 354 | 598 | 1184 |
| | Collected Bounce | 105 | 198 | 221 | 808 |
| | In Goal | 3 | 2 | 5 | 25 |
| | Own Player - Collected | 96 | 162 | 88 | 57 |
| | Own Player - Failed | 28 | 75 | 42 | 18 |
| | Pressure Error | 39 | 100 | 79 | 53 |
| | Try Kick | 5 | 12 | 15 | 12 |

**Table D6**
Table of frequency (n) of kick outcome in each collection time range.

| | | Kick Collection Time | | |
|---|---|---|---|---|
| | | 0-3 s | 3-5 s | 5 s+ |
| Kick Outcome | Caught Full | 250 | 1872 | 73 |
| | Collected Bounce | 291 | 651 | 390 |
| | In Goal | 2 | 8 | 25 |
| | Own Player - Collected | 145 | 216 | 42 |
| | Own Player - Failed | 33 | 124 | 6 |
| | Pressure Error | 50 | 203 | 18 |
| | Try Kick | 27 | 13 | 4 |

**Table D7**
Table of frequency (n) of kick group in each distance range.

| | | Kick Distance | | | |
|---|---|---|---|---|---|
| | | 0-15 m | 15-25 m | 25-35 m | 35 m+ |
| Kick Group | Group 1 - Tackle First | 176 | 537 | 626 | 611 |
| | Group 2 - Pass First | 56 | 133 | 156 | 330 |
| | Group 3 - Kick First | 31 | 57 | 101 | 791 |
| | Group 4 - Pass and Kick First | 13 | 35 | 45 | 258 |
| | Group 5 - Try Scored | 1 | 10 | 9 | 8 |
| | Group 6 - No Further Action | 58 | 131 | 111 | 159 |

**Table D8**
Table of frequency (n) of kick group in each collection time range.

| | | Kick Collection Time | | |
|---|---|---|---|---|
| | | 0-3 s | 3-5 s | 5 s+ |
| Kick Group | Group 1 - Tackle First | 325 | 1449 | 176 |
| | Group 2 - Pass First | 107 | 499 | 69 |
| | Group 3 - Kick First | 174 | 596 | 210 |
| | Group 4 - Pass and Kick First | 49 | 254 | 48 |
| | Group 5 - Try Scored | 14 | 11 | 3 |
| | Group 6 - No Further Action | 129 | 278 | 52 |

## D.3 Hypothesis Testing of Kick by Zone, Type, Outcome and Group.

**Table D9**
Table of frequency (n) of kick types by group.

| | | Kick Group | | | | | |
|---|---|---|---|---|---|---|---|
| | | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 |
| Kick Type | Bomb | 208 | 48 | 15 | 6 | 0 | 48 |
| | Box | 797 | 241 | 91 | 65 | 0 | 131 |
| | Chip | 111 | 35 | 21 | 13 | 4 | 39 |
| | Cross Pitch | 46 | 8 | 9 | 2 | 7 | 21 |
| | Low | 175 | 52 | 84 | 26 | 15 | 71 |
| | Territorial | 604 | 281 | 738 | 222 | 2 | 146 |
| | Touch Kick | 9 | 10 | 22 | 17 | 0 | 3 |
| | Total | 1950 | 675 | 980 | 351 | 28 | 459 |

**Table D10**
Table of frequency (n) of kick outcome by group.

| | | Kick Group | | | | | |
|---|---|---|---|---|---|---|---|
| | | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 |
| Kick Outcome | Caught Full | 1091 | 343 | 437 | 194 | 0 | 130 |
| | Collected Bounce | 510 | 176 | 473 | 126 | 0 | 47 |
| | In Goal | 0 | 0 | 0 | 0 | 0 | 35 |
| | Own Player - Collected | 221 | 95 | 47 | 14 | 0 | 26 |
| | Own Player - Failed | 45 | 24 | 8 | 6 | 0 | 80 |
| | Pressure Error | 68 | 37 | 14 | 11 | 0 | 141 |
| | Try Kick | 15 | 0 | 1 | 0 | 28 | 0 |
| | Total | 1950 | 675 | 980 | 351 | 28 | 459 |

### D.3.1 Kruskal Wallis and Dunn Test Results - Zone Kicks

**Table D11**
Kruskal Wallis testing comparing spatiotemporal characteristics of kicks by zone. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Degrees of Freedom | $\chi^2$ | $p_{adj}$ |
|---|---|---|---|
| Kick Distance | 4 | 717.36 | .000 |
| Collection Time | 4 | 424.95 | .000 |
| Collection Speed | 4 | 314.73 | .000 |
| Kick Gain | 4 | 134.47 | .000 |

**Table D12**
Dunn testing for distance (m) comparison by kick by zone, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $Z$ | $p_{adj}$ |
|---|---|---|
| Blue - Gold | 12.36 | .000 |
| Blue - Green | -11.10 | .000 |
| Gold - Green | -21.01 | .000 |
| Blue - Red | 11.32 | .000 |
| Gold - Red | 6.57 | .000 |
| Green - Red | 15.30 | .000 |
| Blue - Silver | 12.42 | .000 |
| Gold - Silver | 5.03 | .000 |
| Green - Silver | 18.21 | .000 |
| Red - Silver | -2.89 | .039 |

**Table D13**
Dunn testing for collection time (s) comparison by kick by zone, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $Z$ | $p_{adj}$ |
|---|---|---|
| Blue - Gold | 5.71 | .000 |
| Blue - Green | 1.40 | 1.00 |
| Gold - Green | -3.79 | .002 |
| Blue - Red | 14.60 | .000 |
| Gold - Red | 12.26 | .000 |
| Green - Red | 13.80 | .000 |
| Blue - Silver | 15.12 | .000 |
| Gold - Silver | 11.37 | .000 |
| Green - Silver | 13.66 | .000 |
| Red - Silver | -4.24 | .000 |

**Table D14**
Dunn testing for collection speed ($ms^{-1}$) comparison by kick by zone, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $Z$ | $p_{adj}$ |
|---|---|---|
| Blue - Gold | 7.88 | .000 |
| Blue - Green | -11.26 | .000 |
| Gold - Green | -17.19 | .000 |
| Blue - Red | 2.79 | .053 |
| Gold - Red | -0.17 | 1.00 |
| Green - Red | 6.99 | .000 |
| Blue - Silver | 2.11 | .346 |
| Gold - Silver | -2.39 | .169 |
| Green - Silver | 8.45 | .000 |
| Red - Silver | -1.25 | 1.00 |

**Table D15**
Dunn testing for gain (m) comparison by kick by zone, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $Z$ | $p_{adj}$ |
|---|---|---|
| Blue - Gold | -6.86 | .000 |
| Blue - Green | 4.49 | .000 |
| Gold - Green | 10.14 | .000 |
| Blue - Red | -3.78 | .002 |
| Gold - Red | -1.18 | 1.00 |
| Green - Red | -5.40 | .000 |
| Blue - Silver | -4.47 | .000 |
| Gold - Silver | -0.45 | 1.00 |
| Green - Silver | -6.83 | .000 |
| Red - Silver | 0.78 | 1.00 |

### D.3.2 Kruskal Wallis and Dunn Test Results - Kick Types

**Table D16**
Kruskal Wallis testing comparing spatiotemporal characteristics of kicks by type. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Degrees of Freedom | $\chi^2$ | $p_{adj}$ |
|---|---|---|---|
| Kick Distance | 6 | 2133.30 | .000 |
| Collection Time | 6 | 802.03 | .000 |
| Collection Speed | 6 | 1769.30 | .000 |
| Kick Gain | 6 | 142.55 | .000 |

**Table D17**

Dunn testing for distance (m) comparison by kick type, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Bomb - Box | 1.74 | 1.00 |
| Bomb - Chip | 4.48 | .000 |
| Box - Chip | 3.89 | .002 |
| Bomb - Cross Pitch | -5.02 | .000 |
| Box - Cross Pitch | -6.50 | .000 |
| Chip - Cross Pitch | -7.94 | .000 |
| Bomb - Low | 4.70 | .000 |
| Box - Low | 4.27 | .000 |
| Chip - Low | -0.52 | 1.00 |
| Cross Pitch - Low | 8.17 | .000 |
| Bomb - Territorial | -20.31 | .000 |
| Box - Territorial | -37.33 | .000 |
| Chip - Territorial | -22.73 | .000 |
| Cross Pitch - Territorial | -5.89 | .000 |
| Low - Territorial | -29.17 | .000 |
| Bomb - Touch Kick | -10.86 | .000 |
| Box - Touch Kick | -12.40 | .000 |
| Chip - Touch Kick | -13.19 | .000 |
| Cross Pitch - Touch Kick | -5.62 | .000 |
| Low - Touch Kick | -13.60 | .000 |
| Territorial - Touch Kick | -2.31 | .437 |

**Table D18**
Dunn testing for collection time (s) comparison by kick type, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Bomb - Box | 6.02 | .000 |
| Bomb - Chip | 17.29 | .000 |
| Box - Chip | 15.62 | .000 |
| Bomb - Cross Pitch | 13.68 | .000 |
| Box - Cross Pitch | 11.53 | .000 |
| Chip - Cross Pitch | 0.86 | 1.00 |
| Bomb - Low | 19.50 | .000 |
| Box - Low | 19.09 | .000 |
| Chip - Low | -0.78 | 1.00 |
| Cross Pitch - Low | -1.49 | 1.00 |
| Bomb - Territorial | 7.55 | .000 |
| Box - Territorial | 2.24 | .539 |
| Chip - Territorial | -14.89 | .000 |
| Cross Pitch - Territorial | -10.91 | .000 |
| Low - Territorial | -18.43 | .000 |
| Bomb - Touch Kick | 5.67 | .000 |
| Box - Touch Kick | 3.20 | .029 |
| Chip - Touch Kick | -4.93 | .000 |
| Cross Pitch - Touch Kick | -4.96 | .000 |
| Low - Touch Kick | -4.73 | .000 |
| Territorial - Touch Kick | 2.61 | .189 |

**Table D19**

Dunn testing for collection speed ($ms^{-1}$) comparison by kick type, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.d

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Bomb - Box | -0.96 | 1.00 |
| Bomb - Chip | -4.99 | .000 |
| Box - Chip | -5.18 | .000 |
| Bomb - Cross Pitch | -14.41 | .000 |
| Box - Cross Pitch | -15.24 | .000 |
| Chip - Cross Pitch | -10.21 | .000 |
| Bomb - Low | -6.09 | .000 |
| Box - Low | -6.98 | .000 |
| Chip - Low | -0.18 | 1.00 |
| Cross Pitch - Low | 10.87 | .000 |
| Bomb - Territorial | -22.71 | .000 |
| Box - Territorial | -36.66 | .000 |
| Chip - Territorial | -13.09 | .000 |
| Cross Pitch - Territorial | 3.17 | .032 |
| Low - Territorial | -16.99 | .000 |
| Bomb - Touch Kick | -13.20 | .000 |
| Box - Touch Kick | -13.62 | .000 |
| Chip - Touch Kick | -9.75 | .000 |
| Cross Pitch - Touch Kick | -0.90 | 1.00 |
| Low - Touch Kick | -10.17 | .000 |
| Territorial - Touch Kick | -3.72 | .000 |

**Table D20**

Dunn testing for gain (m) comparison by kick type, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Bomb - Box | 2.51 | .252 |
| Bomb - Chip | -0.26 | 1.00 |
| Box - Chip | -2.46 | .289 |
| Bomb - Cross Pitch | -0.55 | 1.00 |
| Box - Cross Pitch | -2.05 | .852 |
| Chip - Cross Pitch | -0.34 | 1.00 |
| Bomb - Low | 0.86 | 1.00 |
| Box - Low | -1.64 | 1.00 |
| Chip - Low | 1.04 | 1.00 |
| Cross Pitch - Low | 1.12 | 1.00 |
| Bomb - Territorial | 7.06 | .000 |
| Box - Territorial | 7.53 | .000 |
| Chip - Territorial | 6.31 | .000 |
| Cross Pitch - Territorial | 4.59 | .000 |
| Low - Territorial | 6.70 | .000 |
| Bomb - Touch Kick | 4.79 | .000 |
| Box - Touch Kick | 3.92 | .002 |
| Chip - Touch Kick | 4.78 | .000 |
| Cross Pitch - Touch Kick | 4.45 | .000 |
| Low - Touch Kick | 4.41 | .000 |
| Territorial - Touch Kick | 1.89 | 1.00 |

### D.3.3 Kruskal Wallis and Dunn Test Results - Kick Outcomes

**Table D21**

Kruskal Wallis testing comparing spatiotemporal characteristics of kicks by outcome. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Degrees of Freedom | $\chi^2$ | $p_{adj}$ |
|---|---|---|---|
| Kick Distance | 6 | 691.52 | .000 |
| Collection Time | 6 | 165.27 | .000 |
| Collection Speed | 6 | 473.89 | .000 |
| Kick Gain | 6 | 318.68 | .000 |

**Table D22**
Dunn testing for distance (m) comparison by kick outcome, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Caught Full - Collected Bounce | -4.35 | .000 |
| Caught Full - In Goal | -2.26 | .499 |
| Collected Bounce - In Goal | -1.37 | 1.00 |
| Caught Full - Own Player - Collected | 18.35 | .000 |
| Collected Bounce - Own Player - Collected | 20.15 | .000 |
| In Goal - Own Player - Collected | 7.83 | .000 |
| Caught Full - Own Player - Failed | 12.16 | .000 |
| Collected Bounce - Own Player - Failed | 13.72 | .000 |
| In Goal - Own Player - Failed | 7.37 | .000 |
| Own Player - Collected - Own Player - Failed | -0.08 | 1.00 |
| Caught Full - Pressure Error | 11.85 | .000 |
| Collected Bounce - Pressure Error | 13.72 | .000 |
| In Goal - Pressure Error | 6.39 | .000 |
| Own Player - Collected - Pressure Error | -2.94 | .068 |
| Own Player - Failed - Pressure Error | -2.26 | .498 |
| Caught Full - Try Kick | 4.04 | .001 |
| Collected Bounce - Try Kick | 5.00 | .000 |
| In Goal - Try Kick | 4.42 | .000 |
| Own Player - Collected - Try Kick | -2.39 | .356 |
| Own Player - Failed - Try Kick | -2.19 | .598 |
| Pressure Error - Try Kick | -0.91 | 1.00 |

**Table D23**
Dunn testing for collection time (s) comparison by kick outcome, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Caught Full - Collected Bounce | -7.46 | .000 |
| Caught Full - In Goal | -7.04 | .000 |
| Collected Bounce - In Goal | -5.49 | .000 |
| Caught Full - Own Player - Collected | 3.98 | .001 |
| Collected Bounce - Own Player - Collected | 8.35 | .000 |
| In Goal - Own Player - Collected | 8.03 | .000 |
| Caught Full - Own Player - Failed | 0.27 | 1.00 |
| Collected Bounce - Own Player - Failed | 3.39 | .015 |
| In Goal - Own Player - Failed | 6.56 | .000 |
| Own Player - Collected - Own Player - Failed | -2.09 | .774 |
| Caught Full - Pressure Error | -1.75 | 1.00 |
| Collected Bounce - Pressure Error | 2.19 | .595 |
| In Goal - Pressure Error | 6.05 | .000 |
| Own Player - Collected - Pressure Error | -4.18 | .001 |
| Own Player - Failed - Pressure Error | -1.36 | 1.00 |
| Caught Full - Try Kick | 4.74 | .000 |
| Collected Bounce - Try Kick | 6.40 | .000 |
| In Goal - Try Kick | 8.48 | .000 |
| Own Player - Collected - Try Kick | 3.19 | .030 |
| Own Player - Failed - Try Kick | 4.12 | .001 |
| Pressure Error - Try Kick | 5.14 | .000 |

**Table D24**
Dunn testing for collection speed ($ms^{-1}$) comparison by kick outcome, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Caught Full - Collected Bounce | 0.34 | 1.00 |
| Caught Full - In Goal | 3.80 | .003 |
| Collected Bounce - In Goal | 3.71 | .004 |
| Caught Full - Own Player - Collected | 14.96 | .000 |
| Collected Bounce - Own Player - Collected | 14.06 | .000 |
| In Goal - Own Player - Collected | 0.93 | 1.00 |
| Caught Full - Own Player - Failed | 11.68 | .000 |
| Collected Bounce - Own Player - Failed | 11.25 | .000 |
| In Goal - Own Player - Failed | 1.61 | 1.00 |
| Own Player - Collected - Own Player - Failed | 1.47 | 1.00 |
| Caught Full - Pressure Error | 12.30 | .000 |
| Collected Bounce - Pressure Error | 11.71 | .000 |
| In Goal - Pressure Error | 0.81 | 1.00 |
| Own Player - Collected - Pressure Error | -0.24 | 1.00 |
| Own Player - Failed - Pressure Error | -1.57 | 1.00 |
| Caught Full - Try Kick | 1.45 | 1.00 |
| Collected Bounce - Try Kick | 1.37 | 1.00 |
| In Goal - Try Kick | -1.88 | 1.00 |
| Own Player - Collected - Try Kick | -3.72 | .004 |
| Own Player - Failed - Try Kick | -4.28 | .000 |
| Pressure Error - Try Kick | -3.51 | .009 |

**Table D25**
Dunn testing for gain (m) comparison by kick outcome, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Caught Full - Collected Bounce | 3.72 | .004 |
| Caught Full - In Goal | -7.15 | .000 |
| Collected Bounce - In Goal | -7.87 | .000 |
| Caught Full - Own Player - Collected | -8.57 | .000 |
| Collected Bounce - Own Player - Collected | -10.44 | .000 |
| In Goal - Own Player - Collected | 4.28 | .000 |
| Caught Full - Own Player - Failed | -5.16 | .000 |
| Collected Bounce - Own Player - Failed | -6.60 | .000 |
| In Goal - Own Player - Failed | 4.29 | .000 |
| Own Player - Collected - Own Player - Failed | 0.49 | 1.00 |
| Caught Full - Pressure Error | -10.97 | .000 |
| Collected Bounce - Pressure Error | -12.53 | .000 |
| In Goal - Pressure Error | 2.85 | .091 |
| Own Player - Collected - Pressure Error | -3.08 | .044 |
| Own Player - Failed - Pressure Error | -2.90 | .078 |
| Caught Full - Try Kick | -4.56 | .000 |
| Collected Bounce - Try Kick | -5.37 | .000 |
| In Goal - Try Kick | 2.31 | .433 |
| Own Player - Collected - Try Kick | -1.45 | 1.00 |
| Own Player - Failed - Try Kick | -1.62 | 1.00 |
| Pressure Error - Try Kick | 0.07 | 1.00 |

### D.3.4 Kruskal Wallis and Dunn Test Results - Kick Groups

**Table D26**
Kruskal Wallis testing comparing spatiotemporal characteristics of kicks by group based on action following kick collection. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Variable | Degrees of Freedom | $\chi^2$ | $p_{adj}$ |
|---|---|---|---|
| Kick Distance | 5 | 858.07 | .000 |
| Collection Time | 5 | 31.60 | .000 |
| Collection Speed | 5 | 743.75 | .000 |
| Kick Gain | 5 | 261.05 | .000 |

**Table D27**

Dunn testing for distance (m) comparison by kick groups based on action following kick collection, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Group 1 - Group 2 | -6.58 | .000 |
| Group 1 - Group 3 | -26.40 | .000 |
| Group 2 - Group 3 | -14.79 | .000 |
| Group 1 - Group 4 | -14.31 | .000 |
| Group 2 - Group 4 | -8.14 | .000 |
| Group 3 - Group 4 | 3.29 | .015 |
| Group 1 - Group 5 | 0.94 | 1.00 |
| Group 2 - Group 5 | 2.45 | .214 |
| Group 3 - Group 5 | 6.33 | .000 |
| Group 4 - Group 5 | 5.13 | .000 |
| Group 1 - Group 6 | 0.87 | 1.00 |
| Group 2 - Group 6 | 5.61 | .000 |
| Group 3 - Group 6 | 19.08 | .000 |
| Group 4 - Group 6 | 12.34 | .000 |
| Group 5 - Group 6 | -0.69 | 1.00 |

**Table D28**

Dunn testing for collection time (s) comparison by kick groups based on action following kick collection, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Group 1 - Group 2 | 0.68 | 1.00 |
| Group 1 - Group 3 | 0.19 | 1.00 |
| Group 2 - Group 3 | -0.46 | 1.00 |
| Group 1 - Group 4 | 0.83 | 1.00 |
| Group 2 - Group 4 | 0.27 | 1.00 |
| Group 3 - Group 4 | 0.66 | 1.00 |
| Group 1 - Group 5 | 3.94 | .001 |
| Group 2 - Group 5 | 3.73 | .003 |
| Group 3 - Group 5 | 3.87 | .002 |
| Group 4 - Group 5 | 3.57 | .005 |
| Group 1 - Group 6 | 4.05 | .001 |
| Group 2 - Group 6 | 2.97 | .045 |
| Group 3 - Group 6 | 3.59 | .005 |
| Group 4 - Group 6 | 2.28 | .337 |
| Group 5 - Group 6 | -2.77 | .084 |

**Table D29**

Dunn testing for collection speed ($ms^{-1}$) comparison by kick groups based on action following kick collection, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Group 1 - Group 2 | -7.00 | .000 |
| Group 1 - Group 3 | -25.15 | .000 |
| Group 2 - Group 3 | -13.44 | .000 |
| Group 1 - Group 4 | -14.02 | .000 |
| Group 2 - Group 4 | -7.61 | .000 |
| Group 3 - Group 4 | 2.76 | .086 |
| Group 1 - Group 5 | -1.16 | 1.00 |
| Group 2 - Group 5 | 0.47 | 1.00 |
| Group 3 - Group 5 | 3.98 | .000 |
| Group 4 - Group 5 | 3.01 | .039 |
| Group 1 - Group 6 | -1.52 | 1.00 |
| Group 2 - Group 6 | 3.86 | .002 |
| Group 3 - Group 6 | 16.02 | .000 |
| Group 4 - Group 6 | 10.35 | .000 |
| Group 5 - Group 6 | 0.73 | 1.00 |

**Table D30**

Dunn testing for gain (m) comparison by kick groups based on action following kick collection, utilised after Kruskal Wallis testing. A significance level of 5% was used, and $p_{adj}$ is reported with Bonferroni correction.

| Comparison | $z$ | $p_{adj}$ |
|---|---|---|
| Group 1 - Group 2 | 1.65 | 1.00 |
| Group 1 - Group 3 | 2.76 | 0.09 |
| Group 2 - Group 3 | 0.69 | 1.00 |
| Group 1 - Group 4 | 1.87 | 0.92 |
| Group 2 - Group 4 | 0.53 | 1.00 |
| Group 3 - Group 4 | 0.01 | 1.00 |
| Group 1 - Group 5 | -3.61 | 0.00 |
| Group 2 - Group 5 | -3.95 | 0.00 |
| Group 3 - Group 5 | -4.15 | 0.00 |
| Group 4 - Group 5 | -4.05 | 0.00 |
| Group 1 - Group 6 | -13.76 | 0.00 |
| Group 2 - Group 6 | -13.02 | 0.00 |
| Group 3 - Group 6 | -14.53 | 0.00 |
| Group 4 - Group 6 | -11.60 | 0.00 |
| Group 5 - Group 6 | -0.13 | 1.00 |

## D.4 Cluster Analysis using Gain

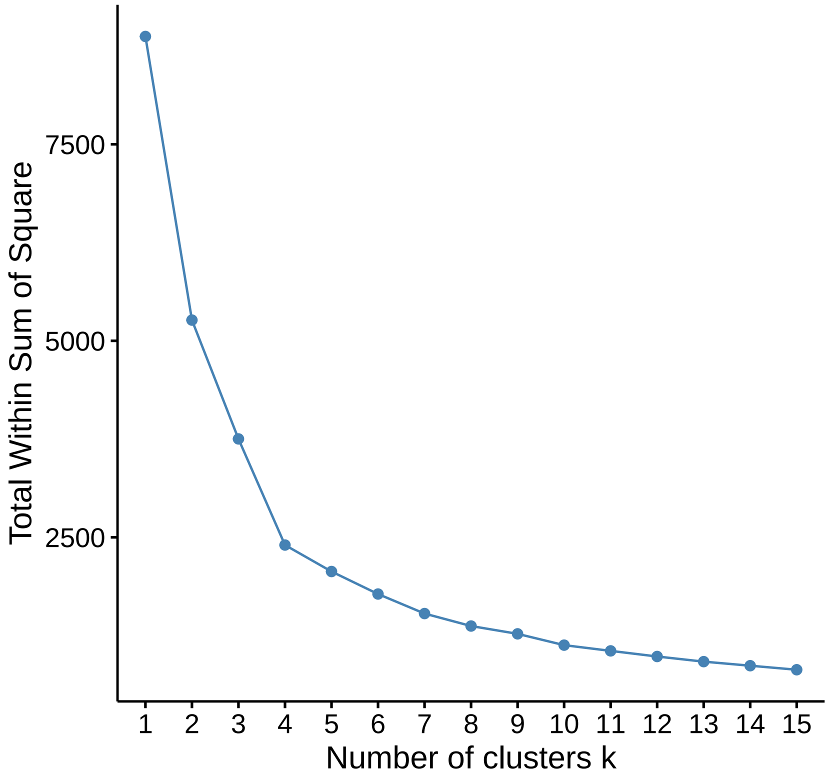



**Figure D2**
Elbow plot illustrating the total within sum of squares (WSS) as a function of the number of clusters (k) for the dataset. The plot displays a characteristic 'elbow' pattern, indicating the optimal number of clusters. The elbow point represents the point of diminishing returns in terms of WSS reduction.Plot suggest an optimal K value of 4.

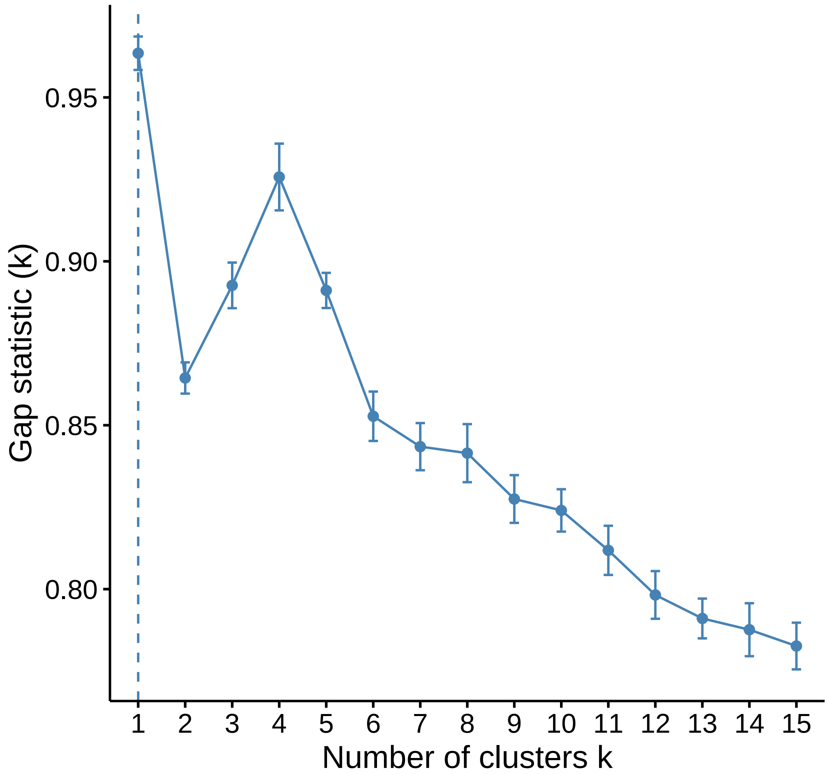



**Figure D3**

Gap statistic plot displaying the optimal number of clusters for the given dataset. The $y$-axis represents the gap statistic, and the $x$-axis represents the number of clusters (k). Plot suggests an optimal K value of 4.

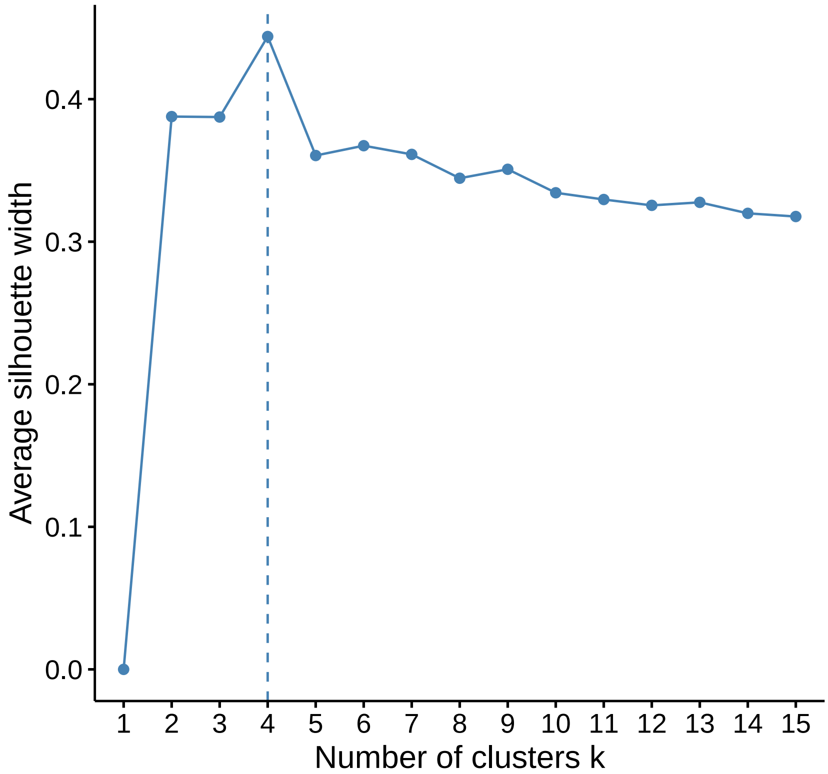



**Figure D4**
Silhouette plot illustrating the quality of clustering for various numbers of clusters. The $y$-axis shows the average silhouette score, and the $x$-axis represents the number of clusters (k). Higher silhouette scores indicate better-defined clusters, with the optimal number of clusters identified by the highest average silhouette score. Plot suggests an optimal K value of 4.

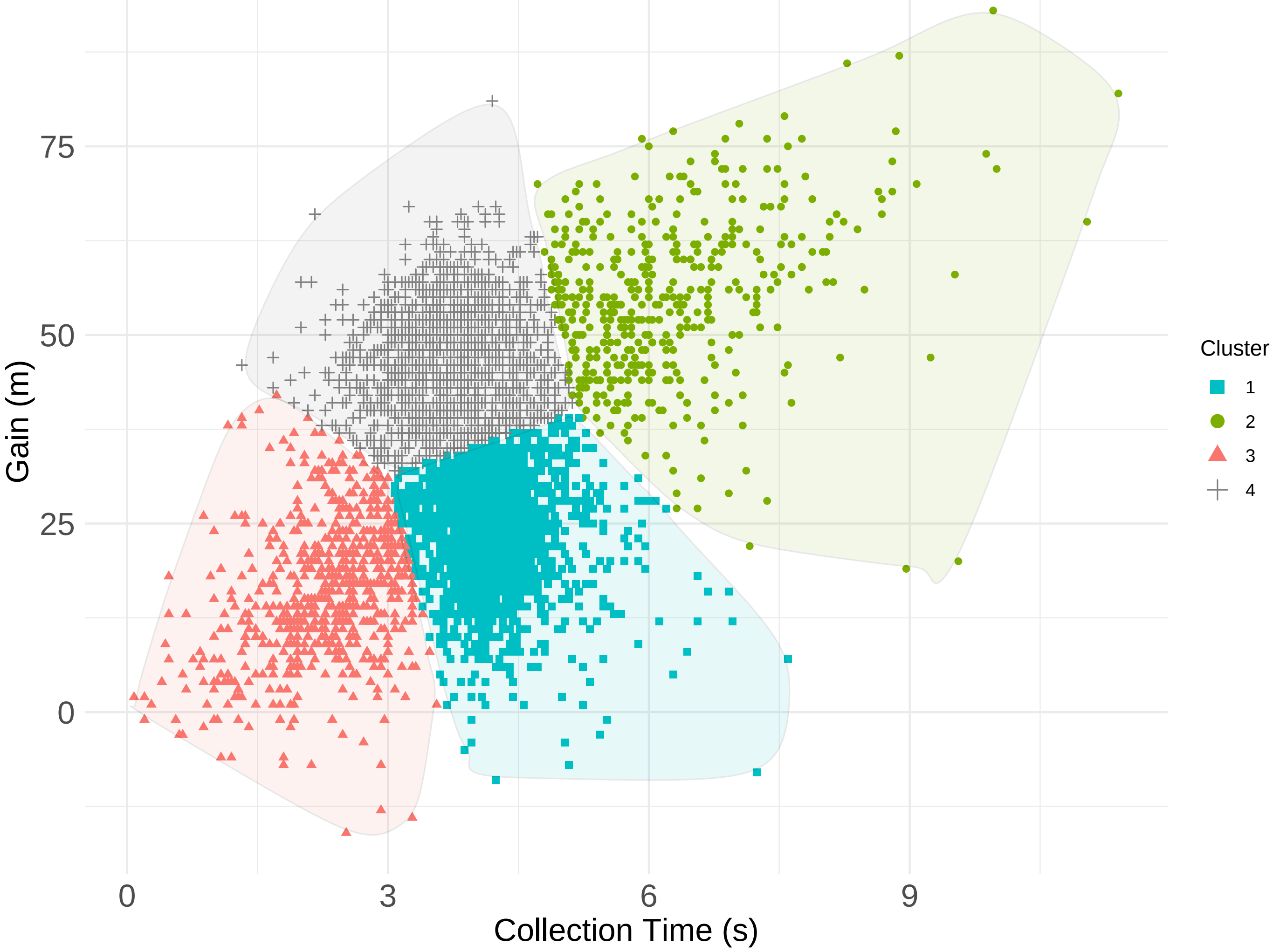



**Figure D5**
Cluster diagram illustrating the results of K-Means clustering analysis, based on scaled distance-time measurement of the kicks in the dataset. Each data point is represented by a coloured marker corresponding to its assigned cluster. The plot provides a visual representation of the distinct clusters and their spatial distribution in the feature space. The analysis identified four clusters (Cluster 1, Cluster 2, Cluster 3 and Cluster 4), each exhibiting unique characteristics and spatial arrangement.

## D.5 Running Analysis for Forwards

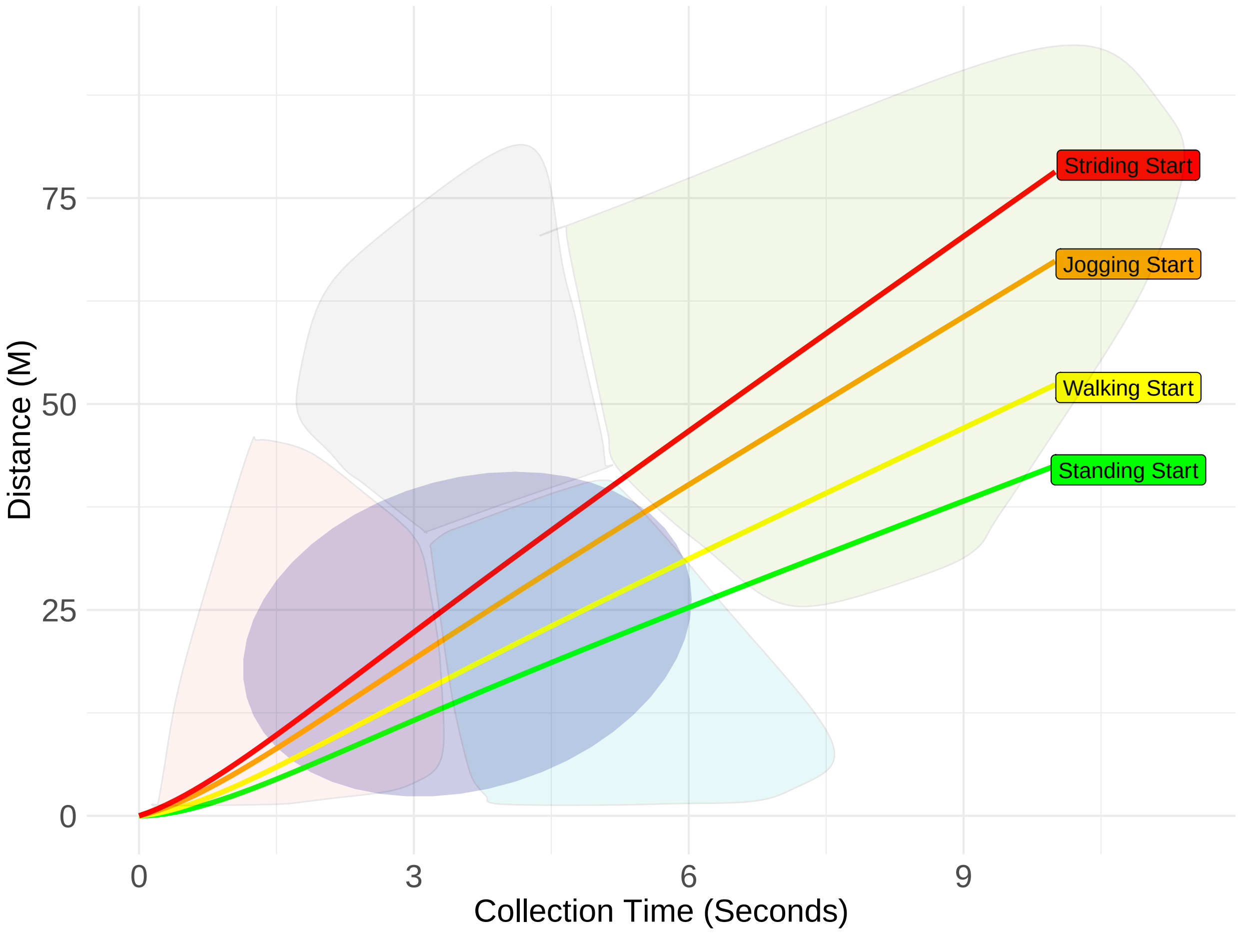



**Figure D6**
Distance-time Plot with previous clusters of ″Fast″ and ″Slow″ Territorials (grey and green respectively), ″Fast″ and ″Slow″ Contestables (red and light blue) represented by the related coloured polygons. The dark blue polygons represent the 90% confidence ellipse of kicks successfully collected by the kicking team. The four lines identify the distance capacity for a forward given the different starting mechanisms, (green for standing, yellow for walking, orange for jogging and red for striding start), these are based on tau and max values from literature (Clavel et al., 2022; Duthie et al., 2006).

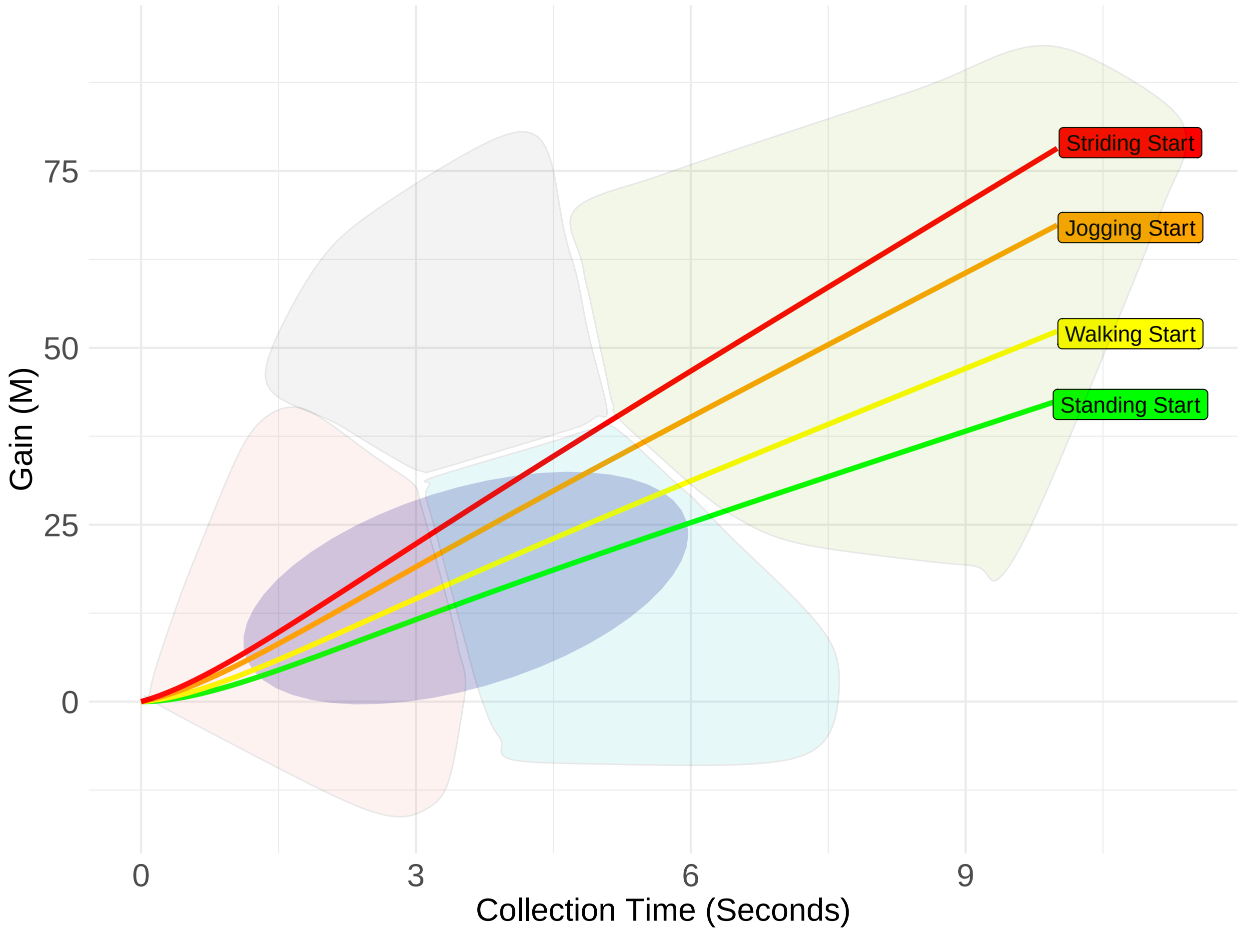



**Figure D7**
Gain-time Plot with previous clusters of "Fast" and "Slow" Territorials (grey and green respectively), "Fast" and "Slow" Contestables (red and light blue) represented by the related coloured polygons. The dark blue polygons represent the 90% confidence ellipse of kicks successfully collected by the kicking team. The four lines identify the gain capacity for a forward given the different starting mechanisms, (green for standing, yellow for walking, orange for jogging and red for striding start), these are based on tau and max values from literature (Clavel et al., 2022; Duthie et al., 2006).

# References

Ball, K., Ingleton, C., Peacock, J., & Nunome, H. (2013). Ball impact dynamics in the punt kick. *Conference: 31 International Conference on Biomechanics in Sports (2013).*

BBC. (2021). Pro14 becomes united rugby championship as south africa sides join tournament - bbc sport. https://www.bbc.co.uk/sport/rugby-union/57475511

BBC. (2023, February). Six nations 2023: “smart” rugby ball being used in this year’s competition. https://www.bbc.co.uk/sport/av/rugby-union/64351834

Bennett, M., Bezodis, N. E., Shearer, D. A., & Kilduff, L. P. (2020). Predicting performance at the group-phase and knockout-phase of the 2015 rugby world cup. *European Journal of Sport Science*, *21*, 312–320. https://doi.org/10.1080/17461391.2020.1743764

Bennett, M., Bezodis, N. E., Shearer, D. A., Locke, D., & Kilduff, L. P. (2019). Descriptive conversion of performance indicators in rugby union. *Journal of Science and Medicine in Sport*, *22*, 330–334. https://doi.org/10.1016/j.jsams.2018.08.008

Bezodis, N. E., Atack, A., Willmott, A. P., Callard, J. E. B., & Trewartha, G. (2018). Kicking foot swing planes and support leg kinematics in rugby place kicking: Differences between accurate and inaccurate kickers. *European Journal of Sport Science*, *19*, 451–460. https://doi.org/10.1080/17461391.2018.1519039

Bezodis, N. E., Atack, A., & Winter, S. (2017, October). *The biomechanics of place kicking in rugby union*. Routledge. https://doi.org/10.4324/9781315638553-4

Bishop, L., & Barnes, A. (2013). Performance indicators that discriminate winning and losing in the knockout stages of the 2011 rugby world cup. *International Journal of Performance Analysis in Sport*, *13*, 149–159. https://doi.org/10.1080/24748668.2013.11868638

Botzoris, G., & Profillidis, V. (2019). *Modeling of transport demand*. Elsevier.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32. https://doi.org/10.1023/A:1010933404324

Breiman, L., Cutler, A., Liaw, A., & Wiener, M. (2022). Package ′randomforest′.

Bunker, R. P., Fujii, K., Hanada, H., & Takeuchi, I. (2021). Supervised sequential pattern mining of event sequences in sport to identify important patterns of play: An application to rugby union. *PLoS ONE*, *16*. https://doi.org/10.1371/JOURNAL.PONE.0256329

Bunker, R. P., & Spencer, K. (2021). Performance indicators contributing to success at the group and play-off stages of the 2019 rugby world cup. *Journal of Human Sport and Exercise*, *17*, 683–698. https://doi.org/10.14198/jhse.2022.173.18

Bunker, R. P., & Thabtah, F. (2019). A machine learning framework for sport result prediction. *Applied Computing and Informatics*, *15*, 27–33. https://doi.org/10.1016/j.aci.2017.09.005

Burt, E., James, N., & Hughes, M. (2015). 12. In *Performance analysis of sport ix*. Routledge.

Caicedo-Parada, S., Lago-Peñas, C., & Ortega-Toro, E. (2020). Passing networks and tactical action in football: A systematic review. *International Journal of Environmental Research and Public Health*, *17*(18), 6649. https://doi.org/10.3390/ijerph17186649

Calder, J. M., & Durbach, I. N. (2015). Decision support for evaluating player performance in rugby union. *International Journal of Sports Science & Coaching*, *10*, 21–37. https://doi.org/10.1260/1747-9541.10.1.21

Clavel, P., Leduc, C., Morin, J.-B., Owen, C., Samozino, P., Peeters, A., Buchheit, M., & Lacome, M. (2022). Concurrent validity and reliability of sprinting force–velocity profile assessed with gps devices in elite athletes. *International Journal of Sports Physiology and Performance*, *17*, 1527–1531. https://doi.org/10.1123/ijspp.2021-0339

Colomer, C. M., Pyne, D. B., Mooney, M., McKune, A., & Serpell, B. G. (2020). Performance analysis in rugby union: A critical systematic review. *Sports Medicine - Open*, *6*. https://doi.org/10.1186/s40798-019-0232-x

Costello, I., Belton, S.-J., & MacNamara, Á. (2022). Stand up and fight: A case study of a professional rugby club negotiating a covid-19 crisis, a talent development perspective. *Sports*, *10*(8), 124. https://doi.org/10.3390/sports10080124

Coughlan, M., Mountifield, C., Sharpe, S., & Mara, J. K. (2019). How they scored the tries: Applying cluster analysis to identify playing patterns that lead to tries in super rugby. *International Journal of Performance Analysis in Sport*, *19*, 435–451. https://doi.org/10.1080/24748668.2019.1617018

Cunningham, D. J., Shearer, D. A., Drawer, S., Pollard, B., Cook, C. J., Bennett, M., Russell, M., & Kilduff, L. P. (2018). Relationships between physical qualities and key performance indicators during match-play in senior international rugby union players. *PLOS ONE*, *13*. https://doi.org/10.1371/journal.pone.0202811

Dalton-Barron, N., Palczewska, A., Weaving, D., Rennie, G., Beggs, C., Roe, G., & Jones, B. (2022). Clustering of match running and performance indicators to assess between- and within-playing position similarity in professional rugby league. *Journal of Sports Sciences*, *40*, 1712–1721. https://doi.org/10.1080/02640414.2022.2100781

den Hollander, S., Brown, J., Lambert, M., Treu, P., & Hendricks, S. (2016). Skills associated with line breaks in elite rugby union. *Journal of Sports Science Medicine*, *15*, 501–508.

den Hollander, S., Jones, B., Lambert, M., & Hendricks, S. (2018). The what and how of video analysis research in rugby union: A critical review. *Sports Medicine - Open*, *4*. https://doi.org/10.1186/s40798-018-0142-3

Diedrick, E., & van Rooyen, M. (2011). Line break situations in international rugby. *International Journal of Performance Analysis in Sport*, *11*, 522–534. https://doi.org/10.1080/24748668.2011.11868570

Dixon, M. J., & Coles, S. G. (1997). Modelling association football scores and inefficiencies in the football betting market. *Journal of the Royal Statistical Society Series C: Applied Statistics*, *46*, 265–280. https://doi.org/10.1111/1467-9876.00065

Duthie, G. M., Pyne, D. B., Marsh, D. J., & Hooper, S. L. (2006). Sprint patterns in rugby union players during competition. *Journal of Strength and Conditioning Research*, *20*, 208–214. https://doi.org/10.1519/00124278-200602000-00034

Green, A., Kerr, S., Olivier, B., Dafkin, C., & Mckinon, W. (2016). The trade-off between distance and accuracy in the rugby union place kick. *Kinesiology*, *48*, 251–257. https://doi.org/10.26582/k.48.2.4

Gregorutti, B., Michel, B., & Saint-Pierre, P. (2016). Correlation and variable importance in random forests. *Statistics and Computing*, *27*, 659–678. https://doi.org/10.1007/s11222-016-9646-1

Hendricks, S., Matthews, B., Roode, B., & Lambert, M. (2014). Tackler characteristics associated with tackle performance in rugby union. *European Journal of Sport Science*, *14*, 753–762. https://doi.org/10.1080/17461391.2014.905982

Hendricks, S., Till, K., Oliver, J. L., Johnston, R. D., Attwood, M., Brown, J., Drake, D., MacLeod, S., Mellalieu, S. D., Treu, P., & et al. (2018). Technical skill training framework and skill load measurements for the rugby union tackle. *Strength & Conditioning Journal*, *40*, 44–59. https://doi.org/10.1519/ssc.0000000000000400

Hendricks, S., van Niekerk, T., Sin, D. W., Lambert, M., den Hollander, S., Brown, J. C., Maree, W., Treu, P., Till, K., & Jones, B. (2017). Technical determinants of tackle and ruck performance in international rugby union. *Journal of Sports Sciences*, *36*(5), 522–528. https://doi.org/10.1080/02640414.2017.1322216

Hill, N. E., Rilstone, S., Stacey, M. J., Amiras, D., Chew, S., Flatman, D., & Oliver, N. S. (2018). Changes in northern hemisphere male international rugby union players' body mass and height between 1955 and 2015. *BMJ Open Sport and Exercise Medicine*, *4*. https://doi.org/10.1136/bmjsem-2018-000459

Holmes, C., Jones, R., Harland, A., & Petzing, J. (2006). Ball launch characteristics for elite rugby union players. In E. F. Moritz & S. Haake (Eds.), *The engineering of sport 6* (pp. 211–216). Springer New York.

Hughes, A., Barnes, A., Churchill, S. M., & Stone, J. A. (2017). Performance indicators that discriminate winning and losing in elite men's and women's rugby union. *International Journal of Performance Analysis in Sport*, *17*, 534–544. https://doi.org/10.1080/24748668.2017.1366759

Hughes, M. T., Hughes, M. D., Williams, J., James, N., Vuckovic, G., & Locke, D. (2012). Performance indicators in rugby union. *Journal of Human Sport and Exercise*, *7*, 383–401. https://doi.org/10.4100/JHSE.2012.72.05

Hughes, M. D., & Bartlett, R. (2015). *The use of performance indicators in performance analysis*. Routledge. https://doi.org/10.4324/9781315776743-7

James, N., Mellalieu, S., & Jones, N. (2005). The development of position-specific performance indicators in professional rugby union. *Journal of Sports Sciences*, *23*, 63–72. https://doi.org/10.1080/02640410410001730106

Jay, N. D., Papillon-Cavanagh, S., Olsen, C., Bontempi, G., & Haibe-Kains, B. (2013). Mrmre: An r package for parallelized mrmr ensemble feature selection. *Bioinformatics*, *29*, 2365–2368. https://doi.org/10.1093/bioinformatics/btt383

Jones, N. M., James, N., & Mellalieu, S. D. (2008). An objective method for depicting team performance in elite professional rugby union. *Journal of Sports Sciences*, *26*, 691–700. https://doi.org/10.1080/02640410701815170

Korte, F., & Lames, M. (2019). Passing network analysis of positional attack formations in handball. *Journal of Human Kinetics*, *70*, 209–221. https://doi.org/10.2478/hukin-2019-0044

Kraak, W., Venter, R., & Coetzee, F. (2016). Scoring and general match profile of super rugby between 2008 and 2013. *International Journal of Performance Analysis in Sport*, *16*, 786–805. https://doi.org/10.1080/24748668.2016.11868923

Lazarczuk, S. L., Love, T., Cross, M. J., Stokes, K. A., Williams, S., Taylor, A. E., Fuller, C. W., Brooks, J. H., Kemp, S. P., & Bezodis, N. E. (2020). The epidemiology of kicking injuries in professional rugby union: A 15-season prospective study. *Scandinavian Journal of Medicine & Science in Sports*, *30*, 1739–1747. https://doi.org/10.1111/sms.13737

Lindsay, A., Draper, N., Lewis, J., Gieseg, S. P., & Gill, N. (2015). Positional demands of professional rugby. *European Journal of Sport Science*, *15*(6), 480–487. https://doi.org/10.1080/17461391.2015.1025858

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. *Fifth Berkeley Symposium on Mathematical Statistics and Probability*. https://api.semanticscholar.org/CorpusID:6278891

Maher, M. J. (1982). Modelling association football scores. *Statistica Neerlandica*, *36*, 109–118. https://doi.org/https://doi.org/10.1111/j.1467-9574.1982.tb00782.x

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *Source: The Annals of Mathematical Statistics*, *18*, 50–60.

Marino, T. K., Ferreira, A. R., Morgans, R., Schildberg, W. T., Aoki, M. S., Corrêa, U. C., & Moreira, A. (2022). The emergence of critical incidents in rugby union matches using markov chain analysis. *Science and Medicine in Football*, *7*, 323–330. https://doi.org/10.1080/24733938.2022.2135758

McCormick, J. (2019). Revolutionising rugby – a statistical analysis on how the game has evolved. https://www.statsperform.com/resource/revolutionising-rugby-a-statistical-analysis-on-how-the-game-has-evolved/

Morin, J.-B., Samozino, P., Murata, M., Cross, M. R., & Nagahara, R. (2019). A simple method for computing sprint acceleration kinetics from running velocity data: Replication study with improved design. *Journal of Biomechanics*, *94*, 82–87. https://doi.org/10.1016/j.jbiomech.2019.07.020

Morissette, L., & Chartier, S. (2013). The k-means clustering technique: General considerations and implementation in mathematica. *Tutorials in Quantitative Methods for Psychology*, *9*, 15–24. https://doi.org/10.20982/tqmp.09.1.p015

Mosey, T. J., & Mitchell, L. J. (2020). Key performance indicators in australian sub-elite rugby union. *Journal of Science and Medicine in Sport*, *23*, 35–40. https://doi.org/10.1016/j.jsams.2019.08.014

Nakagawa, A. (2006). Re-examination of importance of kick-off and 50m restart kick play in rugby football games. *International Journal of Sport and Health Science*, *4*, 273–285. https://doi.org/10.5432/ijshs.4.273

Naughton, M., Jones, B., Hendricks, S., King, D., Murphy, A., & Cummins, C. (2020). Quantifying the collision dose in rugby league: A systematic review, meta-analysis, and critical analysis. *Sports Medicine - Open*, *6*(1), 6. https://doi.org/10.1186/s40798-019-0233-9

Ortega, E., Villajero, D., & Palao, J. M. (2009). Differences in game statistics between winning and losing rugby teams in the six nations tournament. *Journal of Sports Science and Medicine*, *8*, 523–527.

Parmar, N., James, N., Hearne, G., & Jones, B. (2018). Using principal component analysis to develop performance indicators in professional rugby league. *International Journal of Performance Analysis in Sport*, *18*(6), 938–949. https://doi.org/10.1080/24748668.2018.1528525

Pavely, S., Adams, R. D., Di Francesco, T., Larkham, S., & Maher, C. G. (2010). Bilateral clearance punt kicking in rugby union: Effects of hand used for ball delivery. *International Journal of Performance Analysis in Sport*, *10*, 187–196. https://doi.org/10.1080/24748668.2010.11868513

Phatak, A. A., Mehta, S., Wieland, F.-G., Jamil, M., Connor, M., Bassek, M., & Memmert, D. (2022). Context is key: Normalization as a novel approach to sport specific preprocessing of kpi's for match analysis in soccer. *Scientific Reports*, *12*. https://doi.org/10.1038/s41598-022-05089-y

Pocock, C., Bezodis, N. E., Davids, K., & North, J. S. (2018). Hot hands, cold feet? investigating effects of interacting constraints on place kicking performance at the 2015 rugby union world cup. *European Journal of Sport Science*, *18*, 1309–1316. https://doi.org/10.1080/17461391.2018.1486459

Pocock, C., Bezodis, N. E., Davids, K., Wadey, R., & North, J. S. (2020). Understanding key constraints and practice design in rugby union place kicking: Experiential knowledge of professional kickers and experienced coaches. *International Journal of Sport Science & Coaching*, *15*. https://doi.org/10.1177/1747954120943073

Prieto, J., Gómez, M.-Á., & Sampaio, J. (2015). From a static to a dynamic perspective in handball match analysis: A systematic review. *The Open Sports Sciences Journal*, *8*, 25–34. https://doi.org/10.2174/1875399X01508010025

Quarrie, K. L., & Hopkins, W. G. (2015). Evaluation of goal kicking performance in international rugby union matches. *Journal of Science and Medicine in Sport*, *18*, 195–198. https://doi.org/10.1016/j.jsams.2014.01.006

Reid, A. (2020, August). South africa pair southern kings and cheetahs dropped from pro14 | scotland | the times. https://www.thetimes.co.uk/article/south-africa-pair-southern-kings-and-cheetahs-dropped-from-pro14-9tc7d00sl

Rennie, G., Weaving, D., Hart, B., Dalton-Barron, N., & Jones, B. (2022). Tackle and ball carrier demands of rugby league: A seven-year league-wide study including over 1,000,000 tackle events. *Journal of Science and Medicine in Sport*, *25*, 850–854. https://doi.org/10.1016/J.JSAMS.2022.07.002

Roberts, S. P., Trewartha, G., Higgitt, R. J., El-Abd, J., & Stokes, K. A. (2008). The physical demands of elite english rugby union. *Journal of Sports Sciences*, *26*, 825–833. https://doi.org/10.1080/02640410801942122

Rodrigues, F., & Pinto, Â. (2022). Prediction of football match results with machine learning. *Procedia Computer Science*, *204*, 463–470.

R-Open-Science. (n.d.). Basics • rselenium. https://docs.ropensci.org/RSelenium/articles/basics.html

Rugby-World. (2021, March). Rugby explained: The evolution of the kick chase. https://www.rugbyworld.com/featured/rugby-explained-the-evolution-of-the-kick-chase-122843

Sakar, C. O., Kursun, O., & Gurgen, F. (2012). A feature selection method based on kernel canonical correlation analysis and the minimum redundancy-maximum relevance filter method. *Expert Systems with Applications*, *39*, 3432–3437. https://doi.org/10.1016/j.eswa.2011.09.031

Sarmento, H., Clemente, F. M., Araújo, D., Davids, K., McRobert, A., & Figueiredo, A. (2018). What performance analysts need to know about research trends in association football (2012–2016): A systematic review. *Sports Medicine*, *48*(4), 799–836. https://doi.org/10.1007/s40279-017-0836-6

Scott, G. A., Edwards, O., Bezodis, N. E., Waldron, M., Roberts, E., Pyne, D. B., Mara, J., Cook, C., Mason, L., & Brown, M. R. (2023). Classifying winning performances in international women's rugby union. *International Journal of Sports Physiology and Performance*, *18*, 1072–1078. https://doi.org/10.1123/ijspp.2023-0086

Sedeaud, A., De Larochelambert, Q., Schipman, J., & Toussaint, J.-F. (2021). The covid-19 pandemic impact on away and home victories in soccer and rugby union. *Frontiers in Sports and Active Living*, *3*, 695922. https://doi.org/10.3389/fspor.2021.695922

Seo, K., Kobayashi, O., Murakami, M., Yorita, D., Nagai, H., & Asai, K. (2010). Simulation of the trajectory of a punted rugby ball taking into account the asymmetrical pressure distribution caused by the seams. *Journal of Visualization*, *13*, 97–105. https://doi.org/10.1007/s12650-009-0019-0

Seo, K., Yorita, D., Shimoyama, K., Nagai, H., & Asai, K. (2010). Multi-objective exploration of the launch condition for a fluctuating punted kick in rugby on the basis of psp measurement. *Procedia Engineering*, *2*, 2499–2504. https://doi.org/10.1016/j.proeng.2010.04.022

Sharma, M., Monika, Kumar, N., & Kumar, P. (2021). Naive bayes-correlation based feature weighting technique for sports match result prediction. *Evolutionary Intelligence*, *15*(3), 2171–2186. https://doi.org/10.1007/s12065-021-00629-3

Sinclair, J., Taylor, P., Smith, A., Bullen, J., Bentley, I., & Hobbs, S. (2017). Three-dimensional kinematic differences between accurate and high velocity kicks in rugby union place kicking. *International Journal of Sports Science & Coaching*, *12*, 371–380. https://doi.org/10.1177/1747954117710515

Smart, D., Hopkins, W. G., Quarrie, K. L., & Gill, N. (2011). The relationship between physical fitness and game behaviours in rugby union players. *European Journal of Sport Science*, *14*, S8–S17. https://doi.org/10.1080/17461391.2011.635812

Stanhope, J., & Hughes, M. (1997). An analysis of scoring in the 1991 rugby union world cup for men. *Notational Analysis of Sport I II*, 166–167.

Stats Perform. (n.d.). Stats Perform Website [Accessed: 2025-01-27].

Tee, J. C., Lambert, M. I., & Coopoo, Y. (2016). Gps comparison of training activities and game demands of professional rugby union. *International Journal of Sports Science & Coaching*, *11*, 200–211. https://doi.org/10.1177/1747954116637153

Turner, A. N., Jones, B., Stewart, P., Bishop, C., Parmar, N., Chavda, S., & Read, P. (2019). Total score of athleticism: Holistic athlete profiling to enhance decision-making. *Strength & Conditioning Journal*, *41*, 91–101. https://doi.org/10.1519/ssc.0000000000000506

Ungureanu, A. N., Brustio, P. R., Mattina, L., & Lupo, C. (2019). "how" is more important than "how much" for game possession in elite northern hemisphere rugby union. *Biology of Sport*, *36*, 265–272. https://doi.org/10.5114/biolsport.2019.87048

United Rugby Championship. (2025). Competition rules [Accessed: 2025-01-12]. https://www.unitedrugby.com/about/competition-rules van Rooyen, K. M. (2012). A statistical analysis of tackling performance during international rugby union matches from 2011. *International Journal of Performance Analysis in Sport*, *12*, 517–530. https://doi.org/10.1080/24748668.2012.11868616

van Rooyen, K. M., & Noakes, D. T. (2006). An analysis of the movements, both duration and field location, of 4 teams in the 2003 rugby world cup. *International Journal of Performance Analysis in Sport*, *6*, 40–56. https://doi.org/10.1080/24748668.2006.11868354

van Rooyen, M., Yasin, N., & Viljoen, W. (2014). Characteristics of an 'effective' tackle outcome in six nations rugby. *European Journal of Sport Science*, *14*, 123–129.

Vaz, L., Hendricks, S., & Kraak, W. (2019). Statistical review and match analysis of rugby world cups finals. *Journal of Human Kinetics*, *66*, 247–256. https://doi.org/10.2478/hukin-2018-0061

Vaz, L., Carreras, D., & Kraak, W. (2012). Analysis of the effect of alternating home and away field advantage during the six nations rugby championship. *International Journal of Performance Analysis in Sport*, *12*, 593–607. https://doi.org/10.1080/24748668.2012.11868621

Vaz, L., Mouchet, A., Carreras, D., & Morente, H. (2011). The importance of rugby game-related statistics to discriminate winners and losers at the elite level competitions in close and balanced games. *International Journal of Performance Analysis in Sport*, *11*, 130–141. https://doi.org/10.1080/24748668.2011.11868535

Waldron, M., Worsfold, P. R., Twist, C., & Lamb, K. (2014). The relationship between physical abilities, ball-carrying and tackling among elite youth rugby league players. *Journal of Sports Sciences*, *32*(6), 542–549. https://doi.org/10.1080/02640414.2013.841975

Watson, N., Durbach, I., Hendricks, S., & Stewart, T. (2017). On the validity of team performance indicators in rugby union. *International Journal of Performance Analysis in Sport*, *17*, 609–621. https://doi.org/10.1080/24748668.2017.1376998

Watson, N., Hendricks, S., Stewart, T., & Durbach, I. (2020). Integrating machine learning and decision support in tactical decision-making in rugby union. *Journal of the*

*Operational Research Society*, *72*, 2274–2285. https://doi.org/10.1080/01605682.2020.1779624

Wheeler, K. W., Askew, C. D., & Sayers, M. G. (2010). Effective attacking strategies in rugby union. *European Journal of Sport Science*, *10*, 237–242. https://doi.org/10.1080/17461391.2010.482595

Wheeler, K. W., Mills, D., Lyons, K., & Harrinton, W. (2013). Effective defensive strategies at the ruck contest in rugby union. *International Journal of Sports Science & Coaching*, *8*, 481–492. https://doi.org/10.1260/1747-9541.8.3.481

Wheeler, K. W., & Sayers, M. (2009). Contact skills predicting tackle-breaks in rugby union. *International Journal of Sports Science & Coaching*, *4*, 535–544. https://doi.org/10.1260/174795409790291420

Wheeler, K. W., & Sayers, M. G. (2011). Rugby union contact skills alter evasive agility performance during attacking ball carries. *International Journal of Sports Science & Coaching*, *6*, 419–432. https://doi.org/10.1260/1747-9541.6.3.419

World-Rugby. (2017a). Player numbers. *World Rugby.* https://www.world.rugby/news/35960

World-Rugby. (2017b, July). Six law amendments added to global trial as northern hemisphere programme gets underway | world rugby. https://www.world.rugby/news/266973/six-law-amendments-added-to-global-trial-as-northern-hemisphere-programme-gets-underway

World-Rugby. (2021, July). Welfare-focused rugby law trials to be implemented globally | world rugby. https://www.world.rugby/news/653078/welfare-focused-rugby-law-trials-to-be-implemented-globally

World-Rugby. (2022). Laws of the game | world rugby laws. https://www.world.rugby/the-game/laws/law/12