Unpredictability in basketball: An exploration of the effects of ball movement entropy on performance in international women’s basketball

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SUPERVISORS STATEMENT

This is to certify that the thesis entitled “Unpredictability in basketball: An exploration of the effects of ball movement entropy on performance in international women’s basketball” submitted by Wade Hobbs in fulfilment of the requirements for the degree of Doctor of Philosophy is in a form ready for examination.

30th June 2019

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DECLARATION

I, Wade Hobbs, hereby declare that the work contained within this thesis is my own. This thesis does not, to the best of my knowledge, contain any material from any other source, except where due reference is made. This thesis was completely and solely for the degree of Doctor of Philosophy and has not been submitted for a higher degree or diploma at any other academic institution.

Wade Hobbs
30th June 2019
SUBMISSIONS AND PUBLICATION

Parts of the work presented in this thesis have been published and/or presented in the following forums:

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As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

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ABSTRACT

Analysing strategy and tactics is an integral part of modern basketball performance analysis. Until recently however, the majority of research focused purely on outcomes rather than the behaviour that led to these outcomes. More specifically, the majority of research to date has focused on analysing counts of performance indicators, such as assists, rebounds, free-throws, made baskets etc, and while this provides some value, they tell us little about how those indicators were generated and fail to provide coaches with actionable insights.

Consequently, the aim of this thesis was to investigate coach-driven questions focused on developing performance intelligence by analysing team strategy and tactics, otherwise known as ‘collective behaviour’, in international women’s basketball. The current thesis is presented as individual chapters containing stand-alone studies which have been or will be submitted to peer-reviewed academic journals for publication.

Following a general introduction in chapter 1, a review of literature is presented in the second chapter detailing all relevant research that had attempted to measure or analyse tactics and/or strategy in any team sport prior to the first study of the current thesis (August 2015). The review identified two distinct types of research; (i) studies that focused on developing new methods for analysing strategy and tactics, and (ii) research focused on presenting tactical findings, often using previously developed methods. In addition, due to technological advancements, studies differed significantly in terms of the data utilised. With the advent and application of spatio-temporal tracking, a shift was emerging from observational data to spatio-temporal data. This led to a range of new methodologies and applications for performance analysis. With the increased utilisation of spatio-temporal tracking data, there was a shift in focus of research to one that sought to understand collective behaviour in team
The findings of the literature review were used to direct the series of studies that follow in this thesis, which are comprised of a mix of both methodological and practical investigations using spatio-temporal ball tracking data. Furthermore, to maximise practical implications and impact, we focused on answering coach-driven questions through a partnership with Basketball Australia and the Australian Institute of Sport. This resulted in the eventual theme of the thesis, examining unpredictability in basketball and its effects on performance. Consequently, in chapter three we present a method for measuring spatial entropy across the basketball court and apply the method to ball-tracking data collected for six international women’s basketball teams. The study determined that winning teams played with significantly higher entropy in the front-court than losing teams.

Having defined a spatial measure of unpredictability that was associated with outcome measures of team performance, chapter four established a spatial measure of performance for which we could attempt to test the relationship between the two variables. In addition, a novel measure of performance was developed utilising tracking data capable of quantifying spatial effectiveness of ball movement as well as identifying common ball movement sequences. This study identified which areas of the court were the most effective for each team, irrespective of where or when the shot was taken. This highlighted the strengths and weaknesses of different teams, and provided insight into specific ball movement patterns and their distributions for each team. The results provide evidence of team specific strategies for
scoring, with team specific ball movement sequences further adding to available performance intelligence.

Chapter five presents an appropriate statistical method for comparing the previously established spatial measures of performance. A Bayesian hierarchical model was introduced. These models are common in other fields, but as yet, to our knowledge, had not been applied to team sport research. These models are ideal for data with spatial dependency – meaning data in which the regular statistical assumptions of independence amongst observations are violated due to spatial nature of the data. Furthermore, we demonstrated how different spatial scales can significantly impact the results, and therefore, the conclusions drawn from these results. We tested a 6x6, 4x4, and basketball-specific spatial scale. The results from these analyses showed a generally positive association such that increases in spatial entropy were associated with increases in spatial effectiveness. That is, teams that played with less predictability were more successful. Furthermore, we found the strength and confidence of the associations between the two variables were impacted by the spatial scale used, with the 6x6 and 4x4 grids showing the strong positive relationships, while the basketball-specific scale was less conclusive.

In chapter six, with evidence of an association between our measures of entropy and effectiveness, we further refine these measures to compare the final five seconds of ball movement entropy to shooting efficiency. This study provided a more focused investigation of the impact of entropy on performance by considering only the final sequence of ball movements leading to a shot. We hypothesised that greater unpredictability of ball movements prior to a shot would lead to more positive outcomes. The results indicated each team performed differently, with Australia, Japan, France, and the USA showing definitive
positive relationships between entropy and scoring efficiency, while Belarus and Turkey showed less conclusive evidence of this relationship. This finding may be due to differing styles of play between teams.

In the discussion chapter (Chapter 7) we review the findings of each study, discuss the new knowledge that has emerged from the thesis, outline their practical implications, discuss future directions for research on this topic, and finally, provide concluding remarks for the thesis.
CHAPTER 1.

Introduction

1.1 Rationale of The Project

Elite team sport is a competitive pursuit with the unanimous aim to win. To win a team must out-score their opponent. To out-score the opponent the team must execute their performance with greater success than the opponent at the appropriate time. For the highest probability of achieving this, the team must be ideally free from injury, in their peak physical and mental condition and appropriately equipped with game intelligence. This is a considerable task and requires input from the coaching staff, as well as a multi-disciplinary team of professionals. First and foremost, to ensure the athlete/team stays free from injury requires input from areas such as sports medicine, physiotherapy and exercise rehabilitation; physical and mental fitness incorporates areas such as physiology, biomechanics, skill acquisition and psychology; and finally, game intelligence is the primary domain of performance analysis. It is the aspect of game intelligence which will be the focus of this thesis.
Performance analysis is the science of analysing and reporting performance in sport. It is largely observational, with the main distinguishing factor from other sports science disciplines, being that actual competition is analysed, usually through observation, either live or post-competition (O'Donoghue, 2014). One of the primary roles of a performance analyst is to collect and communicate game intelligence for coaches and players. The information collected can include opposition analysis, also known as scouting, individual player analysis and self-analysis. This intelligence is then used to formulate a game strategy based on identified strengths and weaknesses of each team. To enhance understanding and implementation of these analyses, research must include reliable methods and results that are relevant to the coaches and athletes.

Traditionally, performance analysis has been an under researched area of knowledge in comparison to other disciplines of sports science. The primary reasons for this were a lack of interest to publish from research journals (prior to 2000 there were no dedicated performance analysis journals) and the practitioner’s view that the work they produced was simply a part of the job and did not require publication (Hughes and Franks, 2004). Since that time, research in performance analysis has increased dramatically.

There are, however, a number of difficulties that arise when attempting to conduct research in this domain. A common issue is the collection and analysis of outcomes-focused performance indicators, despite little understanding of how team behaviours are associated with team outcomes (McGarry, 2009). The outcomes-focused research is characterised by studies of action frequencies and how they related to winners and losers, essentially explaining a team’s win by the performance indicators they produced during the game. While this is important for coaches, particularly as a way of evaluating performance during a game, it does not answer
the more important question of why those performance indicators are integral to winning and how they contribute to a win. Oliver (2004) presented the ‘four factors’ of winning basketball (effective field goal percentage, turnover percentage, offensive and defensive rebounding percentage and free throw rate) based on extensive statistical analysis of NBA games through history. While it is not presented as a simple equation of ‘outsoring the opponent in each factor will equal a win’, it is widely accepted and now part of the elite basketball lexicon. While this is an example of an important outcome driven analysis, it lacks context as it fails to describe the behaviour that lead to the outcome.

Through outcome-focused research we understand the ‘who’, ‘what’, ‘where’ and ‘when’ of performance but not the ‘how’ and ‘why’, highlighting a breakdown in the scientific progression from description to explanation (McGarry, 2009). Mackenzie and Cushion (2013) in a review of performance analysis of association football, suggested that the method of collecting discrete variables adds very little to the understanding of the complex, unpredictable nature of team sports influenced by player-opponent interactions. It also pointed out that this approach has changed very little in the last 25 years despite evidence that analysing the frequency of occurrences may not be the best indicator of effective performance. While a clear answer to these issues is not available with many confounding factors, as rebutted in Carling, Wright, Nelson, and Bradley (2014), a move away from collecting discrete performance indicators, towards attempting to explain team collective behaviour may uncover answers to the questions of ‘how’ and ‘why’.

Coaches and athletes in elite sport are experts in recognising and understanding tactics, making them the primary gatekeepers of this knowledge (Allard and Burnett, 1985). This creates a problem in research where coaches and domain experts, be it researchers or
performance analysts, have no need to publish their findings or do not publish to protect intellectual property. Alternatively, researchers may not have the domain knowledge to produce findings that are applicable and meaningful to coaches. A lack of domain knowledge also has an impact on applied sports science, and in particular to performance analysts. As previously mentioned, one of the main duties of performance analysts working with team sports is to analyse strategy and tactics. The performance analyst may work with one sport, such as those working for professional clubs, or multiple sports, such as those working at sports institutions/Olympic training centres. In both cases there is a need to be adaptable to work in sports in which one has very little background. Therefore, in order to advance performance analysis research and enhance the abilities of sports scientists in the field, there is a need to better understand strategy and tactics in team sports.

A number of questions still remain: what is strategy and tactics? How do we investigate them? If we can quantify them, how do we convey the information to coaches and athletes? The aim of this thesis is to develop effective methods for the investigation of basketball strategy and tactics. Basketball was the sport of choice because of a strategic partnership with Australia’s governing body of basketball, Basketball Australia and the Australian Institute of Sport. It serves as an ideal sport as ball possession is constantly challenged which provides greater representation of the team’s interactive collective behaviour when compared to football. The findings will help researchers and practitioners evaluate team performance and uncover opposition team tactics in basketball and other team sports.

1.2 Aims

The aim of this thesis is to develop effective methods for investigating collective behaviour in basketball. This will help researchers and practitioners evaluate team performance and better
understand that of their opposition. We will answer coach-driven questions examining strategy and tactics in basketball that uncovers the actions leading to successful performance.
Chapter 1 – Introduction

1.3 References


CHAPTER 2.

Review of the Literature to 2015

Collective Behaviour in Team Sports

A fundamental issue in tactical research that needs to be addressed is the use of terms. In a comprehensive discussion of the concepts of strategy and tactics in team sport Gréhaigne, Godbout, and Bouthier (1999) discuss the misuse of the terms ‘tactics’ and ‘strategy’, their etymology and their use in sporting contexts. In summary, the defining difference is time. A strategy implies forethought, a general plan of how to win made ahead of time. Tactics are said to be spontaneous actions made during a match in response to opposition actions, and reliant on the player’s skills. Finally, schemas of play are defined as organised individual or collective patterns practiced and repeated in advance. For the purposes of this review, ‘collective behaviour’ will be used as an umbrella term to collectively refer to these concepts. This area of research is experiencing increased interest with investigations in each of these
distinct aspects of team play. Collective behaviour analyses have been carried out in a variety of sports including but not limited to basketball, association football (soccer), water polo, volleyball and handball.

Investigations of collective behaviour, in science or in practice, are designed to uncover the specific intentions of opposition teams to achieve their strategic goal, be it macro (to win the game), or micro (to score or not be scored against). This in turn assists in formulating strategy, tactics and schemas to counter these intentions. Collective behaviour research has primarily used two data collection methods, observational analysis and tracking data analysis. In this review, observational analysis refers to non-participant observation research designed to describe or analyse collective behaviour through the systematic observation of live or collected footage of sport games without participating in the actions of those being observed. Tracking data analysis refers to studies that utilise data consisting of each player’s location and/or ball location on the playing surface during the game. The detail of this data can vary from full player tracking, where players’ positions are tracked many times (usually 25) per second throughout an entire game, to partial tracings such as ball tracking, or data such as the F24 soccer data feed from the English Premier League collected by Opta (Perform Group, Feltham, United Kingdom) (Lucey, Bialkowski, Carr, Foote, & Matthews, 2012). Each method of data collection has been used in a wide variety of ways, showing the versatility of each data collection method.

Analysing opposition teams through observation to better understand how they play the game is a ubiquitous part of any high-performance program, and the basis of performance analysis (O'Donoghue, 2014). Observational analysis is a powerful tool because it can be performed live and post-game analysis only requires game footage, so the outcomes are highly
accessible. However, it offers little scope to provide information outside of what is already available to coaches in elite sport. Furthermore, if the status quo of opposition analysis is observation, then how does one gain a competitive advantage?

Tracking data refers to the continuous collection of every player’s position on the playing surface, reported as x, y coordinates. Collective behaviour is analysed using player positioning data through data analysis techniques, such as machine learning (Dutt-Mazumder, Button, Robins, & Bartlett, 2011), data mining (Wei, Lucey, Morgan, & Sridharan, 2013), centroid and phase relation (related to the dynamic systems theory) (Frencken, Lemmink, Delleman, & Visscher, 2011), and network analysis (Passos et al., 2011).

Tracking data analysis may be the answer to breaking the status quo and gaining a competitive advantage. These data are extremely rich in detail and have primarily been collected in professional basketball and football leagues. It has been used in a number of projects including a study investigating the features that help determine the likelihood of scoring in football (Lucey, Bialkowski, Monfort, Carr, & Matthews, 2014), quantifying, visualising and communicating spatial shooting range in NBA basketball (Goldsberry, 2012) and a comprehensive breakdown of the basketball rebounds (Maheswaran, Chang, Henehan, & Danesis, 2012). Furthermore, with studies attempting to obtain and use reliable player tracking data from broadcast footage (non-stationary cameras) (Chen, Chou, Fu, Lee, & Lin, 2012; Fu, Chen, Chou, Tsai, & Lee, 2011; Hu, Chang, Wu, & Chi, 2011) it is conceivable that in the future a team will be capable of applying player tracking data in real-time, providing rich, meaningful insights about their opponents prior to and during competition.
Chapter 2 – Review of Literature

The purpose of this review is to summarise the various methods of analysing collective behaviour in team sport, to examine some key findings from each method, and propose possible future directions of research. The review is broken into three main sections. The first section will report the search methods, inclusions and exclusion criteria, and results for this review. The second section will examine each method in detail with examples of the findings possible and the most recent topics of research. The third section will describe current limitations of the methods under review and possible future applications.

2.1 Search methodology
To investigate collective behaviour research in team sports, a systematic search of all published literature was conducted (Fig 1). The search utilised the computerised databases SPORTDiscus, Medline, IEEE Xplore, Google Scholar, Scopus and Web of Science with the search taking place on the 4th of August 2015. Keywords searched include “soccer” OR “football” OR “basketball” OR “volleyball” OR “netball” OR “water polo” OR “handball” OR “hockey” OR “rugby” OR “invasion sport” OR “invasion game” OR “team sport” AND “tactic*” OR “team configuration” OR “team behaviour” OR “strategy”. Additionally, reference lists from each paper were hand searched for additional articles. The search was restricted to journal articles and conference proceedings written in English. The inclusion criteria were articles that reported on a team sport and in-game team tactics, team strategy, team behaviour or team interactions as an outcome; sample came from participants that played in a competitive league, studies that used participants that had never played the game being studied were not included. The exclusion criteria included studies that did not directly report on collective behaviour, for example studies that evaluated tactical decision making; technical and tactical outcomes of various interventions in which tactics simply refers to isolated instances such as shot location or number of passes; out-of-game tactics such as the
use of time-outs in basketball; studies designed to improve an analysis method, that do not implement the method and report results (common in computer and data science studies, using sport only as a vehicle to investigate an algorithm or analysis method). This process produced 84 relevant articles spanning 36 years.
Search Terms Used:

- “soccer” OR
- “football” OR
- “basketball” OR
- “volleyball” OR
- “netball” OR
- “water polo” OR
- “handball” OR
- “hockey” OR
- “rugby” OR
- “invasion sport” OR
- “invasion game” OR
- “team sport”

AND

Studies identified through database searching (n = 1910)

Studies identified through other sources (n = 10) → Studies after duplicates removed (n = 1713) → Studies removed by first pass (n = 1327)

Studies remaining (n = 142) → Studies removed by second pass (review of abstract) (n = 244)

Studies included in review (n = 84) → Studies excluded based on inclusion exclusion criteria (n = 58)

Figure 1. Description of papers included in the review.
2.2 Results
The search resulted in 84 studies fitting the inclusion criteria. Of those, 44 came from association football, 21 from basketball, 11 from volleyball, 2 from handball, 2 from water polo, 2 from rugby union, 1 from futsal (indoor football) and 1 from floorball (a game similar to hockey) (Fig 2). The studies found generally fit into one of two groups, having either a methodological focus, meaning the purpose of the paper was to introduce a new or updated method to analyse collective behaviour, or outcomes focused, meaning they focused primarily on the collective behaviour related outcomes typically using a previously established method. Forty-one of the included papers were classified as methodological, and 43 were classified as outcomes focused. Within this breakdown there was a mix of observational and tracking data-based studies, with an almost even split in the methodological group and almost 80% of the outcomes focused studies using observational analysis.

Figure 2. Breakdown of sports examined in collective behaviour research.
2.3 Methodological Collective behaviour research

As previously stated, we define this category as any study that proposes a new or updated method to analyse collective behaviour in team sport. To better understand how this category has been implemented, it can be broken down by (i) data type and (ii) sport: (i) 20 papers were based on observational data and 21 made use of spatiotemporal data, (ii) 26 focused on football, 10 on basketball, 2 on volleyball, 1 on handball, 1 on water polo and 1 on rugby union (appendix A). This form of research is an important aspect of performance analysis as it transfers knowledge to practice and informs future research.

A significant issue in collective behaviour research is the relevance of results. The results of a study that reports on the strategy, tactics and/or schemas used in a game are specific to the study’s population and often not transferrable. This is because a coach often devises and employs strategies based on the team’s strengths, weaknesses and their own coaching philosophy, resulting in unique game play, with vastly different strategies employed within individual team sports. Considering this limitation, reporting new methods can have the greatest impact on the scientific community. Within methodological research there have been many developments and approaches used to examine collective behaviour in team sports. The most common methods have consisted of observational models and machine learning techniques however, a vast array of methods have been used to a lesser extent including network analysis, mixed methods, Voronoi diagrams, dynamic systems theory and metrics-based analysis. While some of the methods described do appear in outcomes focused studies, the majority have been methodologically based studies.
2.3.1 Observational models

Ten studies have introduced a new model of observational analysis or applied a known model in a unique way (appendix A). These papers present a system or process designed to be followed in practice in order to systematically capture and analyse data. This type of research generally introduces the model, gives an explanation of its use, performs validity and reliability tests and then applies the method to demonstrate the outcomes available. It differs from the other methods of collective behaviour analysis in that the outcomes are not easily comparable as they are sport-specific and generally describe a new way of collecting data in a systematic way, allowing for greater reliability or more detailed information than past methods. Of the ten studies, nine reported reliability statistics with one not reporting reliability (Ricardo, Alfredo, & Gaetano, 2012).

An example of this type of investigation is the introduction of ‘space creation dynamics’ (SCDs) (Lamas et al., 2011). Referring to collective behaviour as dynamics, and the formation of players on the court as states, this paper catalogues the dynamics used to create space on the court for scoring opportunities. With clear definitions and application of the SCDs, they can be used in future research as valid criteria for analysing the sequential nature of collective behaviour in basketball with a low demand on financial or technological resources. A follow-up study introduced ‘space protection dynamics’ (SPDs) in basketball, seeking to couple SCDs with SPDs, validate the method and identify offense-defence interaction patterns in basketball (Santana et al., 2015). The SPDs are appropriately detailed for research purposes and the combined method (SCDs and SPDs) provides a framework for analysing basketball play through observation.
While the previous examples provided useful information, the quality of studies varied widely. Remmert (2003) analysed the group-tactical offensive behaviour in elite basketball presenting the method of a process orientated model. The study used a notational analysis method to evaluate finishing actions (tactic/technique used to score), which, in contrast to the previous two studies, does not clearly explain the method and draws inappropriate conclusions by providing very generalised training suggestions based on the results.

Similarly, it used a highly varied mix of games as data, including games from men’s and women’s German leagues, European leagues, American leagues and international games. While this may seem like a comprehensive, cross-sectional approach, its heterogeneity likely masks differences in playing style between genders and countries.

Two studies utilised the ‘System of Tactical Assessment in Soccer’ (FUT-SAT) for data collection and analyses (Costa et al., 2010; Silva, Garganta, Santos, & Teoldo, 2014), for which a critical analysis can be found in section 2.4.1. The instrument is used to assess tactical actions based on ten core football tactical principles (5 offensive and 5 defensive), including penetration, offensive coverage, width and length, depth mobility, offensive unity, delay, defensive coverage, balance, concentration, and defensive unity (Costa, Garganta, Greco, Mesquita, & Maia, 2011). The ten principles were quantified based on observation of 48 performance variables and were tested for reliability.

2.3.2 Network Analysis

In recent times, a new form of analysis based on social network theory has emerged in an attempt to quantify team interactions. Social network analysis is a broad strategy for investigating social structures (Otte and Rousseau, 2002). Each player represents a node in the network with passes between players generally represented as links between the nodes.
This type of analysis in sport aims to uncover insights not observable simply by watching the game by quantifying and visualising team interactions (Gould & Gatrell, 1980).

This network analysis requires an adjacency matrix that represents the connections between players. In the majority of cases this has consisted of a pass from one player to another on the same team. Each offensive possession generates a separate matrix and the sum of all matrices is used to analyse overall team performance (Fig 3) (Clemente, Martins, Kalamaras, Wong, & Mendes, 2015).

![Network graph of a single match](image)

Figure 3. Network graph of a single match: a) Graph (white) with the highest values of total links, network density, and clustering coefficient; b) Graph (green) with the lowest values of total links, network density, and clustering coefficient.

The main outcome generated from network analyses in team sports is a representation of the structure of the team, which seeks to give a coach insight into how their team distributes the ball or how to break-up or fragment the opposition structure (Gould & Gatrell, 1980). Furthermore, it gives an indication of the most integral links within a team and has been used to estimate the impact of taking a link (player) out of the opposition attack (through greater defensive focus on that player).
Eight studies have used network analysis in some way to investigate collective behaviour; four from football, three from basketball and one from volley ball. Of the eight studies, four reported reliability statistics (Clemente, Martins, Kalamaras, & Mendes, 2015; Clemente et al., 2015; Clemente, Martins, Kalamaras, Wong, et al., 2015; Clemente, Martins, & Mendes, 2015) one stated that reliability had been tested but did not report any details (Trequattrini, Lombardi, & Battista, 2015) and three did not provide any reliability information (Fewell, Armbruster, Ingraham, Petersen, & Waters, 2012; Peña and Touchette, 2012; Zhang, Hu, & Liao, 2013). The most significant and common finding was that teams with greater connectedness were more successful. The exception (Trequattrini, et al., 2015) examining one game between FC Barcelona and AC Milan found the network metrics presented favoured FC Barcelona in the game, however they lost the game 0-2. This result may be due to the very low sample size; alternatively, the metrics were not appropriate for explaining success in football.

While network analysis can provide indications of an overall team structure it does have limitations, most principally in relation to its lack of spatiotemporal context. Simply knowing how many passes were made between specific players provides little context relating to where and when these passes were made, significantly limiting the explanatory power of the analysis (Clemente, Martins, Kalamaras, Oliveira, et al., 2015). Another limitation is that outcomes are often intuitive and contribute little to original insights to the sports being analysed. Clemente, Martins, Kalamaras, & Mendes (2015) concluded through network analysis that across various age groups, the point guard is the most important player in building attack. While these results may be of interest to some, they are highly predictable, as
basketball is generally structured specifically for the point guard to be the leader of the offense.

### 2.3.3 Mixed Methods

Two papers evaluated collective behaviour through mixed methods, specifically quantitative and qualitative methods of data collection (Cordes, Lamb, & Lames, 2012; Sarmento et al., 2014). These studies focused on what the strategy is before the game, followed by an evaluation of how well the strategy was adhered to after the game. This methodology is very beneficial as it includes the coach’s evaluation of ‘tactical adherence’ as an outcome; however, it does not evaluate the effectiveness of collective behaviour, only how well the team followed the game plan.

The most robust example of this method is presented in Cordes et al. (2012) as follows: coaches are interviewed to gain qualitative information of their game philosophy which also serves as a baseline for subsequent steps; a pre-match interview is conducted to learn the strategy for the forthcoming game; the coach’s strategic and tactical decisions are evaluated using an observational notational analysis system based off the information gathered during coach’s interviews; finally a post-match interview is conducted to learn the coach’s evaluation of the game (Fig 4). Following this process an analysis was conducted to systematically evaluate the adherence and choice of strategy throughout the season.
A slightly different mixed methods approach involved researchers detecting patterns of play through systematic observation of football games, complimented by semi-structured interviews with coaches to gain further insight into the patterns of play (Sarmento, et al., 2014). Essentially the two methods were combined to answer the same question as opposed to the previous model which only used the coach’s interviews to inform the notational analysis and review process. The model was designed to evolve over the course of the season, and as such the authors state the observational tool was quite different by the end of the season due to the coach’s feedback loop. However Sarmento et al. (2014) report detecting specific characteristics of play representing differing playing philosophies. Concurrently, the coach’s interpretation of play patterns was mainly focused on tactical-strategic and tactical-technical aspects as well as the characteristics of the players on the team.

The mixed methods approach is a robust approach to evaluating the performance of a team based on the coach’s intentions and could easily be applied to other sports. The main limitation with this method is the time and resources needed to carry it out. Cordes et al. (2012) concedes the approach is a laborious process; however, it does resemble the process that should be undertaken by a performance analyst in the field, in that they work with the coach to improve the process of providing feedback on performance continuously throughout the season.
2.3.4 Machine learning

Machine learning is a subfield of computer science that gives computers the ability to learn without being explicitly programmed (Samuel, 1959). The artificial neural network was the most commonly used machine learning technique in team sport analysis found, however there have been many other techniques employed that are similarly complex, hence each technique will not be explained in detail in this review. The majority of the papers identified as using machine learning techniques are methodological in nature, usually presenting a new or modified technique to analyse team sport and presenting the results. Of the 12 studies identified, only one reported reliability (Pfeiffer and Perl, 2006). This paper used observations to collect performance data, whereas the other 11 studies used tracking data, possibly explaining the disparity in reliability reporting. However, studies utilizing tracking data should not be exempt from reporting reliability, as a range of systems are used to collect this data and neither reliability nor validity of methods are reported in these studies. Finally, sample size varies widely with number of matches analysed ranging from 1 (Kim, Kwon, & Li, 2011) to 380 (Lucey, et al., 2012).

Broadly, these studies have attempted to categorise or describe style of play in some way, or identified the actions leading to a score or scoring opportunity. Lucey et al. (2012) used the ball actions from football to characterise team behaviour using entropy maps (Fig 5) which provide a measure of the predictability of a team’s behaviour. This study showed the top five teams in the competition had the highest mean entropies, such that they played with the highest variability, or lowest predictability.
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Figure 5. Entropy maps showing characteristic ball movements of five English Premier League clubs. Maps are normalised for teams attacking from left to right (Lucey, et al., 2012).

A machine learning study in volleyball found it was possible to accurately classify team configurations of play. The results showed the German team under review played with fewer types of configurations more often compared to the team from Italy who used more variability of configurations. The Italian team won the world championship from which the data was collected, suggesting higher variability in tactics correlated better with success (Jäger, Perl, & Schöllhorn, 2007).

A number of studies investigated variables leading to scores or scoring opportunities. Schrapf and Tilp (2013) used an artificial neural network to classify similar ball trajectories for five passes prior to shots on goal in handball. From eight games, 32 clusters were found, of those, 8 clusters represented 49% of all sequences and gave insight into how the team attempted to set up a scoring opportunity. Similarly, Wei, Sha, Lucey, Morgan, & Sridharan (2013) used 14 hours of tracking data in football to identify the most common patterns of play that lead to a score for the teams under review (an unnamed ‘top tier’ European football club). To achieve this task, K-means clustering (a machine learning technique) was used to classify each scoring play from 10 seconds before the goal (Fig 6). This example highlights the power of machine learning; with a relatively basic goal of examining how teams score goals, the process classified the six most common scoring patterns in a significantly reduced time than it would take to identify manually.
Machine learning techniques applied to tracking data in team sports have shown promising results and with the proliferation of GPS, radio frequency and optical tracking systems in elite sport have the potential for important breakthroughs in the analysis of performance. It does however have its limitations, the most crucial of which is the amount of data needed to draw meaningful conclusions. As with statistical analyses, the more data that is available, the stronger the conclusions that can be drawn. Lucey et al. (2012) used data from 380 football matches for the entropy maps shown above. Similarly, Yue, Lucey, Carr, Bialkowski, & Matthews (2014) required data from over 600 games of basketball for their analysis which was used to predict a ball-handlers next move (shoot or pass) based on the positions of their team mates and the defensive players. This is a major limitation for those outside the relatively small number of professional clubs that pay for access to their team’s data. This
leads to the next major limitation which is difficulty of obtaining the data. Currently, access to the systems used to capture player tracking data, such as SportsVU (STATS LLC, 2015) and Prozone (STATS LLC, 2015) can cost hundreds of thousands of dollars, and hence are only available to the most lucrative of professional sports.

2.3.5 Dynamic Systems Theory
Dynamic systems theory (DST) in a sporting context was first applied to racquet sports and is used to describe the relationship between two players (McGarry and Franks, 1995). It showed that players in tennis and squash play in a unique rhythmical pattern until a ‘perturbation’, such as a good shot or poor shot disrupts the rhythm causing an end to the rally unless the rhythm was re-established through a good defensive recovery (Hughes and Franks, 2007). This concept of a rhythmic system between players has since been extended to team sports with the primary focus on interactions between attacker and defender dyads.

While DST has been referenced in relation to tactics in team sport, only one identified study has used DST as the main focus to explain collective behaviour. Gréhaigne, Bouthier, & David (1997) presented a method for analysing the way goals are scored in football based on DST properties. The transitions between configurations of play are observed allowing time to be taken into consideration when analysing the evolution of a goal. It was shown that player’s choices are based on position, movement and speed of team-mates and opponents and a player will pass the ball into open space. Of the 110 configurations analysed, 102 adhered to this principle, showing the position and movement of players are reliable parameters of play. The authors suggest a goal can only be scored if the principles of the system are adhered to, unless there is a mistake by the defending team. The paper provides a foundation to create tools allowing simulation of movements in football as well as the production of a model with
predictive power. While this study did present interesting findings on the relation of DST to collective behaviour, no further studies were found and the majority of studies that reference the DST relate it to dyadic and spatial-temporal relationships that give no indication of the behaviour of the team as a whole.

Evidence of DST has been shown in individual racket sports (Hughes and Franks, 2007) however its extension to team sports remains unknown. With the great range of possible outcomes within every possession as well as traits and motivations of every player in a game, a unifying theory for explaining collective behaviour in team sport is at best, not yet achieved and at worst, unachievable.

2.3.6 Voronoi Diagrams
Voronoi diagrams were introduced to bring context to spatial analyses in team sport, providing an intelligent metric to better understand collective behaviour. A Voronoi diagram partitions space into regions based on the distance to points (players), such that a player’s region is all the space in which they can reach before any other player in the playing space (assuming standardised velocity) (Fig 7).
Three studies have investigated the use of Voronoi diagrams, all of which did not provide reliability information on data collection methods and each had a sample of 19 possessions (Fonseca, et al., 2012; Fonseca, Milho, Travassos, Araújo, & Lopes, 2013; Lopes, Fonseca, Lese, & Baca, 2015). Results from Fonseca et al. (2012) showed attackers had larger dominant regions than defenders, there was greater variability in size among players from the same team, and at the player level the attacker’s dominant regions were more regular than those of the defenders. Fonseca et al. (2013) overlaid Voronoi diagrams of attackers and defenders, which showed the percentage of free area is closely dependent on interactions between pairs of opponents and penetration from an attacker (with or without the ball) causes a change in the defensive structure represented by maximum % of overlapped area. The final study in this series identified typical spatial profiles of basketball teams. It described three states of play: the delayed transition, when the percentage of team area covered called Voronoi area is $< 31\%$ suggesting the team is very concentrated and at a spatial disadvantage (occurs at the beginning of transition phase); A rash transition, when the percentage of Voronoi area is above $69\%$ in the transition phase, indicating spatial advantage; effective
transition is between 31% and 69% and is the expected pattern; In the organised phase > 69% indicates structured attack and 31% - 69% indicates an attempt to score (penetration) (Lopes, et al., 2015).

Voronoi diagram studies provide a possible mechanism to accurately measure the spatial advantages and disadvantages created during team sport games. They were, however, highly methodological studies, with each only using 19 possessions to demonstrate the application of the method. Further exploration with greater sample sizes are needed to understand what the Voronoi diagram can provide in analysing collective behaviour in team sports.

2.4 Outcomes-focused research

Studies were grouped as outcome-focused if the purpose of the study was to analyse and report collective behaviour information, as opposed to developing a new method for analysing collective behaviour.

2.4.1 Observational Analysis

Silva et al. (2014) used the previously mentioned FUT-SAT system to compare the tactical behaviour of under-11-year-old football players in 3 vs. 3 and 6 vs. 6 small-sided games. The study found that players were more aggressive in 3 vs. 3 games, with significantly more frequent actions of penetration and depth mobility. Six vs six games showed higher frequency of actions of offensive unity, suggesting player’s position themselves farther from the centre of play compared to smaller sided games. Costa et al. (2010) compared the tactical behaviours displayed across four different age groups (U/11, U/13, U/15 and U/19) playing 3 vs. 3 small sided games of football. Results showed various differences in tactical behaviour.
across different age groups. The FUT-SAT system was shown to be reliable in the two studies mentioned. It is a detailed system allowing collection of tactical behaviour from the offensive and defensive side of the ball while also recording the place of action on the field and the action outcome. This results in counts of how many times specific tactical actions occurred, their location and their outcome.

A study by Perica, Trninić, & Jelaska (2014) made use of observational analysis to investigate the relations and interconnections between transition offence and defence in basketball. Transition offense is defined by the moment the ball comes into possession and advancement of the ball towards the team’s basket until a number and/or spatial advantage is achieved or set offence (5 on 5) is commenced. Transition defence begins when there is a change of possession and ends no later than when there is defensive balance and proper defensive position in a 5 on 5 situation. The study found that offence and defence are interrelated phases of play. Specifically, successful transition offence is closely linked with successful positional and transitional defence. Conversely, unsuccessful transition offence is influenced by unsuccessful defence. Successful transition defence is determined by the success of the previous offensive phase (meaning shot selection and offensive rebounding tactics are important for setting up transition defence).

### 2.4.2 Spatial analysis

Sixteen studies were found that analysed space in relation to collective behaviour; such as how teams create or negate space, relationships between team centroids in space and the changing surface area of teams in opposition. Of the fifteen studies found, only one (Chinchilla-Mira, Pérez-Turpin, Martínez-Carbonell, & Jove-Tossi, 2012) reported reliability. Data size ranged from 1 match (Clemente, Couceiro, & Martins, 2013) to 24 (Olthof,
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Frencken, & Lemmink, 2015), with six studies using only one match of data to draw conclusions (for details see Appendix).

The majority of these studies used team centroid as a tactical measure. The centroid is the centre of the team unit. By joining each player on a team with an imaginary line creating a polygon, the centroid is the centre of that shape. Centroids are typically defined as the average position of players on the field (excluding the goalkeeper), alternatively the weighted centroid includes the goalkeeper and the ball (Clemente, Santos-Couceiro, Lourenço-Martins, Sousa, & Figueiredo, 2014). The most common finding in these studies was that the offensive and defensive teams’ centroids moved in-phase, in both the longitudinal and latitudinal directions (both in basketball and football), with a stronger relationship in the longitudinal direction (Bourbousson, Seve, & McGarry, 2010; Clemente, Couceiro, Martins, & Mendes, 2013; Frencken, et al., 2011; Olthof, et al., 2015). This indicates that the movement pattern of one team changes in sync with the movement pattern of the other. The next most common spatial variable measured was team surface area or spread of players. All but one study (Frencken, et al., 2011) investigating surface area showed that teams expand surface area in attack and contract in defence (Clemente, Couceiro, & Martins, 2012; Clemente, Couceiro, Martins, & Mendes, 2013; Clemente, Santos-Couceiro, Lourenço-Martins, Sousa, & Figueiredo, 2014; Moura, Martins, Anido, De Barros, & Cunha, 2012). Another study showed there was a greater area and spread when a defence was conceding a goal compared to when a tackle is made (Moura, Martins, Anido, De Barros, & Cunha, 2012). In contrast the attacking team had a larger spread and area when they suffered tackles compared to shots on goal. Age groups were also compared showing an under 19’s group had a greater stretch index and length to width ratio compared to an under 17’s group (Olthof, et al., 2015).
A study by Sampaio and Maçãs (2012) applied an experimental approach to investigate tactical changes through a 13 week constructivist and cognitivist training program. Global Positioning System tracking data from 5 vs. 5 small sided football games was used to assess movement patterns and inter-player coordination. Specifically, approximate entropy (a measure of regularity of movement) measures were lower in post-test suggesting the increase in expertise led to an increased regularity in player movements. Distances of players to the team centroid were the most powerful variable distinguishing pre- and post-test conditions.

Spatial information is of interest when comparing variables such as age, gender, division, nationality etc. However, from a collective behaviour viewpoint it only provides superficial information which is often intuitive or even obvious such as the findings that team centroids were synchronised (we would not expect team units to move away from each other). These spatial metrics may be most useful as variables for more in-depth investigations, such as the centroid or sub-centroid (a separate centroid for the forwards, middle and backs in football for example) to indicate the predictability of movements under different conditions, or surface area used as a variable looking at the effect of various tactics on creating space. In summary, spatial analyses have potential to provide useful information regarding collective behaviour in team sports as shown by Voronoi diagrams, however reducing a team of players down to one metric such as team centroid or surface area is too simplistic and provides little beyond broad descriptive information.

2.4.3 Tactical and Technical

Tactical and technical research is outcome-focused and reports the frequency and effectiveness of certain tactics and technical elements performed during a game. Generally based on observational data, this type of study can give insights into favoured tactics as well
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as technical efficiency. Notational analysis is used heavily in this type of research, with the researcher observing the game and counting the selected variables. This is an extension of traditional statistical or ‘box score’ summarisations of a game.

The outcomes are generally related to scoring or winning, for example a breakdown of the type of offensive attack (tactical) used to score goals in soccer as well as the type and number of passes (technical) used to score (Yiannakos and Armatas, 2006b). This was the most used method found consisting of 27 studies with mixed quality. The sample size of matches ranged from 2 (Katsikadelli, 1998) to 380 (Lago-Peñas and Dellal, 2010) with only 12 of the 27 studies reporting reliability of data collection methods. While describing the results of all 27 studies is beyond the scope of this review, a number of examples are summarised here:

Yiannakos and Armatas (2006b) found that organised offense was the most successful type (44.1%), followed by set plays (35.6%) and counter-attacks (20.3%). Long kicks were found to be the most frequent action performed prior to a goal (34.1%). In a comprehensive analysis of ball screens (tactical) in basketball, Gómez et al. (2015) identified the predictors of success (successful shot) related to time, space, players and tasks involved. It was found that the dribblers’ action after the screen and the orientation of the screen were the most important predictors of ball screen effectiveness. As can be seen, the goal of this type of research is to find the tactical and technical features of the game associated with success.

Observation-based research commonly uses the dichotomous successful or unsuccessful shot/goal as the outcome measure. Scoring is the most important outcome of a possession in team sport and therefore, it is valid to use a score as the benchmark to classify successful tactical and technical elements. However, it assigns a disproportionate amount of credit to the final action of a potentially long process. Gómez et al. (2015) used successful shots to
classify ball screens in basketball, extracting the features of those successful instances to evaluate ball screen effectiveness. Therefore, the ball screen instances that ended with a missed shot were classified as unsuccessful. This makes intuitive sense, however it could be argued that many effective ball screens do not necessarily lead to a made shot, and while an effective screen may produce a more open shot, it does not guarantee the shot will go in. This limitation can be avoided with more precise measures of performance. Tracking data has presented a possible solution in basketball by enabling the calculation of distance from the closest defender to the shooter, which may provide a more precise measure of strategic/tactical success (Lucey, Bialkowski, Carr, Yue, & Matthews, 2014).

2.4.4 Retrospective

Retrospective analyses can be thought of as a subgroup of the tactical and technical studies. Only two studies of this type were found, however they highlight the changing nature of tactical and technical variables over time. While this may not be immediately impactful to coaches and athletes, it provides insight into how the game has changed and developed over time. Barreira, Garganta, Castellano, Machado, & Anguera (2015) investigated the changing dynamics of elite soccer over the last 30 years. Forty-five matches between 1982 and 2010 were observed and the variability in soccer dynamics was examined through the SoccerEye observational criteria. It was found that the variable decade explained 31.4% of variability, followed by match status (28%), competition stage (26.5) and halves of the match (18.1%). The authors conclude that contemporary soccer is based on teamwork compared to previous decades, with higher frequency of attacks down the wing, while noting that match status, competition stage and game period have also influenced patterns of play.
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Wallace and Norton (2014) investigated the change of game structure, speed and patterns of play from the 1966 to 2010 world cup soccer finals. It was reported that play duration decreased while stoppage duration increased, changing the work-to-recovery ratio. Game speed increased by 15% and player density also increased. This provides a summary of how the game has changed in a structural and tactical sense and could provide insights into where the game is going. Wallace and Norton (2014) suggest the results found should lead to a prioritisation of speed as a critical element; the game will require faster decision making and more powerful athletes may dominate due to the longer stoppages.

2.5 Conclusion
The review highlights the wide range of techniques and findings from strategic and tactical research in team sport performance analysis. It was shown that research into team sport strategy and tactics generally fall into two groups based on the purpose of the study, methodological or outcomes-based, and the data used in these studies also tends to fall into two groups, observational or tracking data. A common complaint in performance analysis research, as highlighter earlier, is the over-reliance on analysis of outcomes or KPI’s as an indication of performance. As this review highlighted, there has been a shift in focus to understanding the context of the outcomes, and the events that led to them. This was particularly prominent in the studies using tracking data and focus on developing methods that reveal previously unavailable information and insights. Future research should focus on further understanding the actions and situations that lead to successful play in team sports, adding context to game outcomes; this may best be achieved through the use of tracking data which makes available a range of new possible avenues of research.
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## 2.7 Appendix

Appendix A. Summary of literature

<table>
<thead>
<tr>
<th>Author</th>
<th>Method</th>
<th>Sample</th>
<th>Key Findings</th>
</tr>
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<tbody>
<tr>
<td><strong>Methodological</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1979 Gould &amp; Gatrell</td>
<td>Network analysis</td>
<td>1 game</td>
<td>A case study examining the value of SNA in football. The q-analysis showed Liverpool formed a tight, internal structure; in response Manchester defence incorporated Liverpool players into their structure, causing repeated turnovers and created q-holes in the geometry (obstructions that Liverpool had to work around). Manchester's had stronger connections with the goals, ultimately leading them to victory (it should be noted that this was not the main point of the paper). It was also shown that this analysis allows for the evaluation of the effect each individual player has on team structure and how that is affected if they are out of the game.</td>
</tr>
<tr>
<td>1997 Gréhaigne, Bouthier, &amp; David</td>
<td>Dynamic systems theory</td>
<td></td>
<td>DST analysis of collective movements in football revealed that player choices are made based on position, movement and speed of their team mates and opponents. 102 of 110 dynamic configurations of play respected the principle of passing the ball into open space, suggesting this is a constant of the system.</td>
</tr>
<tr>
<td>2003 Remmert</td>
<td>Observational model</td>
<td>60 games (mix of competitions)</td>
<td>Using a systematic observational model, it was shown there are a much wider variety of offensive and defensive interactions than described in the literature. The group-tactical offensive interaction units (an invented unit of offensive-defensive tactical integration) are used against the man-to-man defence mainly with the intention of preparing or overlapping individual finishing actions to make offensive team play more complex and keep the defending team busy by using fake actions. Finally the direct screen is the most used finishing action.</td>
</tr>
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</table>
The application of ANN was positive in the analysis of complex tactical structures in sports games. In particular it provides a way to investigate the flow of the match.

Classifications of constellations were shown to be possible and may support qualitative analysis of team interactions in a game of volleyball. The German team used fewer types of configurations more often, whereas the Italian team used more constellations but less frequently. The variability in tactics shown by Italy appeared to correlate with success.

Showed hierarchical cluster analysis was effective in classifying team tactical patterns of different national volleyball teams in standardized situations.

The methodology presented allows for the comparison of ball actions available to a player in a given area of the field; Identifies strengths and weaknesses of team strategy based on ball location and type of action used; quantifies each players effect on the game result, combining data from both the amount and quality of their performance. Each outcome is supported by examples from four Polish National team games.

Assessed the effectiveness of offensive plays and erroneous collective behaviour. Found the team established equal inside and outside scoring; all inside scores were a result of a final pass from the right baseline, leading to a one-on-one finish in front of the basket; outside ball movement was seen to be a weakness, leading to well defended shots; transition scores were a result of a last pass in the centre paint (key way area of the offensive team).

Used grey analysis (a data analysis technique used for pattern recognition) to classify basketball teams into global types (centre-scoring, 3-point scoring or defence orientated). The classification was based on 14 performance indicators, and 18 teams were given a score between 0-1 on each of the playing types.

Validated 7 individual and group offensive tactical patterns in basketball, named 'space creation dynamics'. In the analysis of International basketball, found the following SCD's frequency in scoring opportunities:
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<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Game Count</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>Kim, Kwon, &amp; Li</td>
<td>Machine learning</td>
<td>1 game</td>
<td>Proposes a framework for the tactical analysis of soccer using player positioning data. Show an example of the morphological changes to the defensive line (four defenders) made by strikers. The results ranked the number of morphological changes made by two strikers from each team, with the top result showing 1079 changes throughout the match.</td>
</tr>
<tr>
<td>2011</td>
<td>Frencken et al.</td>
<td>Spatial analysis</td>
<td>3 8min games</td>
<td>Described game dynamics through team centroid and surface area metrics. A strong positive correlation of centroid position through 3 small sided games. There was a crossing of the centroids in the forward-backward direction for 10 of the 19 goals. No negative linear relation was found for surface area as was hypothesised.</td>
</tr>
<tr>
<td>2012</td>
<td>Cordes et al.</td>
<td>Mixed methods</td>
<td>1 Season</td>
<td>Used quantitative and qualitative techniques to record and evaluated coaching strategies across a season of football. It was shown that aspects of the match which were directly related to the coaching philosophy were less susceptible to change throughout the season, adherence to strategic plans increased and was high for home games.</td>
</tr>
<tr>
<td>2012</td>
<td>Ricardo, Alfredo, &amp; Gaetano</td>
<td>Observational model</td>
<td>9 games</td>
<td>Assessed the adherence of the team to the tactical plans through 9 water polo matches. Results showed a relationship between scoring and well performed tactical patterns, however this relationship broke down when single tactical patterns were analysed.</td>
</tr>
<tr>
<td>2012</td>
<td>Fewell, Armbruster, Ingraham, Petersen, &amp; Waters</td>
<td>Network analysis</td>
<td>16 games</td>
<td>Examined a basketball team as a network, analysing network properties of degree centrality, clustering, entropy and flow centrality across teams and positions. While no one metric was predictive of success, clustering (connectedness across players) and network entropy (unpredictability of ball movement) was most associated with success.</td>
</tr>
<tr>
<td>2012</td>
<td>Peña &amp; Touchette</td>
<td>Network analysis</td>
<td>Undefined</td>
<td>Used network analysis to develop a visual representation of strategy, from which it was possible to identify play pattern, hot-spots on the play and potential weaknesses. Also examined the importance of each player and the effect of removing players from a game. Games came from the 2010 FIFA World Cup and showed Spain, the eventual winner, had the most...</td>
</tr>
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</table>
passes, highest clustering and highest size of clique (pairwise connected by direct passes). Other countries with similar scores to Spain were also very successful in the tournament. Evidently, a well-connected team is successful.

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Games/Actions</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>P. Lucey et al.</td>
<td>Machine learning</td>
<td>380 games</td>
<td>Characterise team behaviour through entropy maps, giving a measure of predictability of team behaviours in a game. This study showed the top five teams in the competition had the highest mean entropies, meaning they played with the highest variability, or lowest predictability. It also reveals information about the style of play employed, with teams (a) and (b) shown to be a passing team who move the ball around well. Teams (c) and (d) do not play the same kind of expansive passing game, with more direct ball movement. The last team (c) that finished 16th played a similar style to the top teams in (a) and (b) however did not utilise the width of the pitch as much.</td>
</tr>
<tr>
<td>2012</td>
<td>Grunz, Memmert, &amp; Perl</td>
<td>Machine learning</td>
<td>1 game</td>
<td>Used a hierarchical architecture of ANN to find tactical patterns in player positioning data from a soccer game. Had an 84% success rate in classifying long and short game initiations (offensive game phases), compared to an expert's manual coding of game initiations.</td>
</tr>
<tr>
<td>2012</td>
<td>Clemente, Couceiro, &amp; Martins</td>
<td>Spatial analysis</td>
<td>13 games</td>
<td>Introduces the effective area of play metric used to measure the changing state of a team’s ground coverage. Compared the effective area of play of teams with and without the ball. An inverse correlation was seen, suggesting a contraction-expansion relation, representing the defence’s contraction and the offensive goal of width and length.</td>
</tr>
<tr>
<td>2012</td>
<td>Fonseca, Milho, Travassos, &amp; Araújo</td>
<td>Voronoi diagrams</td>
<td>19 actions</td>
<td>Spatial dynamics of futsal was investigated using Voronoi diagrams. Found that attackers had larger dominant regions than defenders, and these regions were more variable in size among players from the same team, but at the player level, the attacker’s dominant regions were more regular than those associated with each of the defenders.</td>
</tr>
<tr>
<td>2012</td>
<td>Sampaio &amp; Maçãs</td>
<td>Technical/tactical</td>
<td>1 pre 1 post game</td>
<td>Assessed tactical behaviour through a 13 week training program measuring player movement patterns and inter-player coordination. ApEn measures were lower in post-test suggesting increased regularity with</td>
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</table>
increased expertise. Distance of player from geometric centre was the most powerful variable distinguishing pre and post-test conditions.

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Dataset Size/Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>Zhang, Hu, &amp; Liao</td>
<td>Network analysis</td>
<td>Undefined</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Used link prediction (estimates the existence of links between network nodes based on observed information) to detect basketball team's tactics from performance data. High connectedness scores were seen between two pairs (the player with the most score assists and the highest and second highest scorers). Used a very small data set (1 quarter of a game of basketball).</td>
</tr>
<tr>
<td>2013</td>
<td>Lucey, Oliver, Carr, Roth, &amp; Matthews</td>
<td>Machine learning</td>
<td>380 games</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Assess team football strategy using ball tracking data from 380 English Premier League games. Present a case study examining the anecdotal belief that teams should aim to win at home and draw away games. Shows that home ground advantage is partly due to conservative strategies employed by away teams. Also attempt to identify teams based on the ball movement data from past games, in an attempt predict a team’s style of play. With a success rate of 39% (improved with statistical information to 47%), compared to 19% based on traditional event labelled data, it is a great improvement. Authors point out that teams are often confused if they play a similar style.</td>
</tr>
<tr>
<td>2013</td>
<td>Wei et al.</td>
<td>Machine learning</td>
<td>9 games</td>
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<tr>
<td></td>
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<td></td>
<td>Used k-means clustering (machine learning) to classify the most common plays (the player movements of the offensive team for the 10 seconds leading up to a goal). Found the 6 most used plays leading to a goal, as well as those associated with particular events such as shots, corners and free kicks. This paper also presented methods for accurate event retrieval and highlight detection.</td>
</tr>
<tr>
<td>2013</td>
<td>Clemente, Couceiro, Martins, &amp; Mendes</td>
<td>Spatial analysis</td>
<td>1 game</td>
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<td></td>
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<td>Measures player distribution on the soccer pitch in relation to ball possession status. Each team's pitch occupancy is described. Found that the team in possession of the ball had the highest possession % in the middle midfield sectors (39%); described as a way for coaches to quickly analyse the collective tendencies of a team.</td>
</tr>
<tr>
<td>2013</td>
<td>Clemente, Couceiro, Martins, &amp; Mendes</td>
<td>Spatial analysis</td>
<td>1 game</td>
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<tr>
<td></td>
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<td></td>
<td>Presents team metrics for the measurement of team tactics, including team centroid, team stretch index and team effective play area. Descriptive</td>
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</tbody>
</table>

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### Chapter 2 – Review of Literature

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Data Size</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>Clemente, Couceiro, Martins, Mendes, &amp; Figueiredo</td>
<td>Spatial analysis</td>
<td>1 game</td>
<td>Analysis from one game is presented. Team centroid was shown to be in-phase; there is an inversion of effective play area, from offence to defence.</td>
</tr>
<tr>
<td>2013</td>
<td>Fonseca, Milho, Travassos, Araújo, &amp; Lopes</td>
<td>Voronoi diagrams</td>
<td>19 actions</td>
<td>Used Voronoi diagrams to describe team's spatial interaction behaviour. Found that % free area (%FA) is closely dependent on interactions between pairs of opponents.</td>
</tr>
<tr>
<td>2014</td>
<td>Sarmento, et al., 2014</td>
<td>Mixed method</td>
<td>36 games</td>
<td>Used sequential analysis of performance data and semi-structured interviews to detect and analyse regular patterns of play in football. Results of the quantitative analysis showed the English team had significantly more counterattacks than the Spanish and Italian teams, supporting the idea that the 'direct play' strategy is employed heavily in Britain. Coaches mainly based their play-pattern opinions on tactical-strategic, tactical-technical aspects and characteristics of the players on their team. Further team specific descriptive results are provided.</td>
</tr>
<tr>
<td>2014</td>
<td>Villarejo, Ortega, Gómez, &amp; Palao</td>
<td>Observational model</td>
<td>30 games</td>
<td>Designed and validated an observational instrument to analyse ball possessions in rugby union. 99 behaviours for observation were identified (60 related to initial phase; 14 related to game phase; 25 related to end phase). Shown to be valid and reliable in describing ball possessions was also able to differentiate winning and losing technical and tactical performances.</td>
</tr>
<tr>
<td>2014</td>
<td>Bialkowski et al.</td>
<td>Machine learning</td>
<td>380 games</td>
<td>Attempts to determine the identity of a team, based on playing style from player positioning data, through occupancy maps. Playing style was established from a training set of team behaviour descriptors. Found that there is overlap in styles between teams and some teams play with multiple styles. Visual description of team styles are provided.</td>
</tr>
<tr>
<td>2014</td>
<td>Clemente, Martins, Couceiro, Mendes, &amp; Figueiredo</td>
<td>Spatial analysis</td>
<td>3 games</td>
<td>Four metrics are introduced to evaluate the attacking coverage provided by teammates to the player in possession of the ball. Game specific results are provided. Overall teammates provided a higher level of cover in vigilance.</td>
</tr>
<tr>
<td>Year</td>
<td>Authors</td>
<td>Methodology</td>
<td>Games</td>
<td>Description</td>
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<tr>
<td>------</td>
<td>---------------------------------------------</td>
<td>------------------</td>
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<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>2014</td>
<td>Clemente, Martins, Couceiro, Mendes, &amp; Figueiredo</td>
<td>Spatial analysis</td>
<td>3</td>
<td>Three metrics are introduced to estimate tactical performance in football; they are penetration, offensive space and offensive unity. Results show unity (aims to ensure there is a reduced space between the different lines of the team i.e. defensive, midfield, forward, providing greater support to the ball carrier) was the most accomplished metric with a mean ratio of 0.83 and penetration was performed with the least success (0.42).</td>
</tr>
<tr>
<td>2014</td>
<td>Clemente, Santos-Couceiro, Lourenço-Martins, Sousa, &amp; Figueiredo</td>
<td>Spatial analysis</td>
<td>1</td>
<td>Presented a modified team centroid metric that improves the goalkeeper and ball location (not included in past studies). Results show a strong positive relation between the two team's centroids over the game analysed, in both the x (length of the pitch) and y (side to side) direction.</td>
</tr>
<tr>
<td>2014</td>
<td>Couceiro, Clemente, Martins, &amp; Tenreiro Machado</td>
<td>Spatial analysis</td>
<td>1</td>
<td>Measures the predictability of player's movements in soccer from player positioning data. Found that goalkeepers are the most predictable, midfielders are the least predictable. However despite the predictability, the goalkeeper is the least stable, while lateral defenders movements are the most stable during a match.</td>
</tr>
<tr>
<td>2014</td>
<td>Folgado, Lemmink, Frencken, &amp; Sampaio</td>
<td>Spatial analysis</td>
<td>6</td>
<td>Used a length per width ratio and the distance between centroid of the two teams to assess tactical collective behaviour at different age groups. Results show length per width ratio values were influenced by the age of players, as younger teams presented a higher value in their dispersion on the pitch. This suggests less consistency in stretching (creating space) and concentrating the team. The older age groups had a larger centroid distance in 3 x 3 teams and similar values in the 4 x 4 teams.</td>
</tr>
<tr>
<td>2015</td>
<td>Trequattrini, Lombardi, &amp; Battista</td>
<td>Network analysis</td>
<td>1</td>
<td>Network analysis was used to prove, at least in part, a team's success depends on interactions between team members. Showed that no players of either team were isolated; the grid of passes performed by FC Barcelona is thicker than that of AC Milan. A number of other metrics based on the</td>
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</table>
network analysis are presented, favouring FC Barcelona; however AC Milan won the game 2-0.

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Data</th>
<th>Key Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>Clemente, Martins, Kalamaras, &amp; Mendes</td>
<td>Network analysis</td>
<td>326 actions</td>
<td>Centrality metrics from network analysis were used to analyse player's cooperation in basketball. Statistical differences in %D Centrality (Ability of each player to build the attacking process) and %D Prestige (degree to which each player is a target of his teammates to pass the ball) were found between different position in basketball. No difference was seen between age groups (U/14, U/16, U/18).</td>
</tr>
<tr>
<td>2015</td>
<td>Santana et al.</td>
<td>Observational model</td>
<td>6 games</td>
<td>Aimed to validate classes of defensive actions, propose novel way to analyse matches based on space creation and space protection dynamics. SPD's were shown to be reliable. Short sequences of SCDs and SPDs were more frequent than longer ones. Sequences with no re-start of the offense accounted for 71% of the total couples; one re-start accounted for 18%, two re-starts - 3%, three re-starts, 2% and four restarts ~0.5%. Further descriptive results are presented.</td>
</tr>
<tr>
<td>2015</td>
<td>Wang, Zhu, Hu, Shen, &amp; Yao</td>
<td>Machine learning</td>
<td>241 games</td>
<td>Machine learning is used to discern tactical patterns in soccer from historical match logs. The pass segments prior to a goal are analysed with the most used tactical patterns resulting in a goal presented. Visualisation of tactics is presented for each team in relation to the most successful patterns. Scores are computed indicating the importance of each player in each pattern, plotted in a heat map.</td>
</tr>
<tr>
<td>2015</td>
<td>Lopes, Fonseca, Lese, &amp; Baca</td>
<td>Voronoi Diagrams</td>
<td>19 Possession</td>
<td>Identified typical spatial profiles of basketball teams. Described three states of play: the delayed transition occurs when the % of team area covered (called Voronoi area) is &lt; 31% suggesting the team is very concentrated and at a spatial disadvantage (occurs at the beginning of transition phase); A rash transition occurs when % of VA is above 69% in transition phase, indicating spatial advantage; effective transition is between 31% and 69% and is the expected pattern; In organised phase &gt; 69% indicates structured attack and 31% - 69% indicates an attempt to score (penetration).</td>
</tr>
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</table>
## Outcomes

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Games</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>Katsikadelli</td>
<td>Technical/tactical</td>
<td>2</td>
<td>Specific tactics were analysed, results show the a significant improvement of reception of serve (% of good reception increased from 81.6% to 86.9%). The % of good receptions on the jump serve (a more aggressive serve) was 82.5% and was 90.7% on classic services. A greater proportion of programmed attacks were executed after an attack serve with a jump (84.2% and 90.3% for the two finals games respectively.)</td>
</tr>
<tr>
<td>2002</td>
<td>Fotinakis, Karipidis, &amp; Taxildaris</td>
<td>Technical/tactical</td>
<td>31</td>
<td>Compared transition variables between winners and losers, found no significant difference in fast break efficiency. The main way a fast break was started was the defensive rebound. The most frequent fast break situations where the offence 3v2 players. Also shown was that the distance of the outlet pass affected offensive patterns of the teams.</td>
</tr>
<tr>
<td>2005</td>
<td>Hughes &amp; Franks</td>
<td>Technical/tactical</td>
<td>96</td>
<td>Analysed passing sequences and found there were more goals scored from longer passing sequences from shorter. Significantly more shots per possession were produced for these longer passing sequences, but the strike ratio of goals from shots is better for &quot;direct play: than for &quot;possession play&quot; (longer passing sequences).</td>
</tr>
<tr>
<td>2006</td>
<td>Yiannakos and Armatas, 2006</td>
<td>Technical/tactical</td>
<td>32</td>
<td>Cross tabulation and chi-squared tests revealed that more goals were achieved in the second half than the first half (57.4% to 42.6%). Organised offence accounted for 44.1% of scores, followed by goals after a set play (35.6%) and counter attacks (20.3%). Actions leading to a score showed long passes had the highest frequency (34.1%). Scoring area was also analysed with 44.4% of goals coming from the penalty area, 32.2% from goal area and 20.4% from outside the penalty area.</td>
</tr>
<tr>
<td>2006</td>
<td>Gomez, Evangelos, &amp; Alberto</td>
<td>Technical/tactical</td>
<td>8</td>
<td>Crosstab commands, chi-squared test and t-tests showed the winning teams made more ball possessions versus different types of defensive systems (zone, man-to-man, mixed) than losing teams; while the less successful team generally played their ball possessions against man-to-man and zone defence in the half-court; winners got more points per possession versus different defensive systems, while losers usually had</td>
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possessions without scoring versus half court defensive systems; winning teams had more passes and spent more time in possession versus different defensive systems than losing teams. Surmises that winning team defend better than losing teams in the half court, especially in man-to-man.

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Type of study</th>
<th>Number of games</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>Huciński &amp; Tymanński</td>
<td>Technical/tactical</td>
<td>8</td>
<td>Polish team had advantage in playing back to the basket, with the opponent having the advantage at playing 2-on-2 pick and roll, and a similar level of effectiveness in all other actions. Overall attacks from outside the key (r=0.78) and effectiveness of 1-on-1 play front to the basket (r=0.66) had the most significant influence on results of Polish matches.</td>
</tr>
<tr>
<td>2009</td>
<td>Koch &amp; Tilp</td>
<td>Technical/tactical</td>
<td>18</td>
<td>From chi-squared tests, no serve was shown to be superior; the type of shot (smash or shot) did not significantly depend on the position of the setting; there was a tendency (p=0.054) towards hard attacks when the ball was preceded by a set far away from the net or from a lateral position near the side lines. The time within a rally did not influence the type or quality of attack, however the quality of the preceding reception did influence the type and quality of attack.</td>
</tr>
<tr>
<td>2010</td>
<td>Costa et al.</td>
<td>Technical/tactical</td>
<td>2853</td>
<td>3 v3 and 6 v 6 small sided football games were compared for tactical behaviour, 5 offensive and 5 defensive variables were compared. Results show players displayed safer behaviours in 6 v 6 and more aggressive behaviours in 3 v 3, in that offensive variables of penetration and depth mobility were significantly more frequent in smaller sided games.</td>
</tr>
<tr>
<td>2010</td>
<td>Lago-Peñas &amp; Dellal</td>
<td>Technical/tactical</td>
<td>380</td>
<td>Using ball tracking data, results showed the most successful teams maintained higher ball possession per match and their pattern of play was more stable. Coefficient of variation in ball possession was lower for the best teams. Team possession was higher when losing than when winning or drawing, home teams had higher possession that visiting teams, possession was reduced when playing a strong opposition. Results how strategies in football are influenced by situational variables.</td>
</tr>
<tr>
<td>2010</td>
<td>Taylor, Mellalieu, James, &amp; Barter</td>
<td>Technical/tactical</td>
<td>47</td>
<td>Match variables were investigated in relation to tactical variables. Occurrences of passes by the team reviewed varied as a function of match</td>
</tr>
<tr>
<td>Year</td>
<td>Authors</td>
<td>Methodology</td>
<td>Data</td>
<td>Summary</td>
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<tr>
<td>2010</td>
<td>Alfonso, Mesquita, Marcelino, &amp; da Silva</td>
<td>Technical/tactical</td>
<td>24 Sets</td>
<td>2010 Alfonso, Mesquita, Marcelino, &amp; da Silva Match variables influencing the setter's tactical action was investigated. Attack tempo was shown to be the crucial variable affecting setter's tactical action. A number of variables (closed blocks from opponent, setting in the ideal zone, attack simulation by middle attacker and block anticipation) resulted in quick attacks and reduced effectiveness of opposition blocks.</td>
</tr>
<tr>
<td>2010</td>
<td>Tenga, Holme, Ronglan, &amp; Bahr</td>
<td>Technical/tactical</td>
<td>163 games</td>
<td>2010 Tenga, Holme, Ronglan, &amp; Bahr Counter attacks accounted for a higher proportion of goals (52%) than elaborate attacks (48%), this was significantly different to the control data set (random set of possessions) that showed 59% of elaborate attacks and 41% counterattacks. It was also shown that counterattacks were more effective than elaborate attacks when playing against an imbalanced defence.</td>
</tr>
<tr>
<td>2010</td>
<td>Bourbousson, Seve, &amp; McGarry</td>
<td>Spatial analysis</td>
<td>1 game</td>
<td>2010 Bourbousson, Seve, &amp; McGarry Centroid, stretch index and relative phase relations between two opposing basketball teams was measured. In-phase relations of the centroids were found in both longitudinal and lateral directions, with higher stability in the longitudinal direction. In-phase relations were also seen in the stretch index in the longitudinal direction but none in the lateral direction. Results demonstrate reciprocity between two opposing teams in the expansion and contraction on offence and defence and the in-phase movements of the team as a whole around the court.</td>
</tr>
<tr>
<td>2011</td>
<td>Janković, Leontijević, Pašić, &amp; Jelušić</td>
<td>Technical/tactical</td>
<td>60 games</td>
<td>2011 Janković, Leontijević, Pašić, &amp; Jelušić Using data provided from the FIFA website, tactical variables were compared for teams that won, drew and lost respectively. There was a significantly different number of successful attacks (resulted in a shot on goal) for the winning teams; the final outcome of major competitions depends on the number of performed attacks; total distance ran by players has no correlation to success; there is no difference in % of ball possession between teams that achieved different results; winners had significantly more passes than the other two groups, however there was no difference when accurate passes were considered and no difference in length of passes between the three groups (indicating tactical preference).</td>
</tr>
<tr>
<td>Year</td>
<td>Authors</td>
<td>Methodology</td>
<td>Games</td>
<td>Description</td>
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<tr>
<td>2012</td>
<td>Afonso, Esteves, Araújo, Thomas, &amp; Mesquita</td>
<td>Technical/tactical</td>
<td>31 games</td>
<td>Examined the tactical variables affecting setting zone in volleyball. Found that server player, serve type, serve depth, reception zone, receiver player and reception type were all predictive of setting zone. Of these, the tennis jump serve, serves from the middle player, deep serves, reception near the end line or sidelines, reception by the zone 4 attackers and low reception all impaired the quality of reception, affecting the setter’s actions.</td>
</tr>
<tr>
<td>2012</td>
<td>Costa, Afonso, Brant, &amp; Mesquita</td>
<td>Technical/tactical</td>
<td>19 games</td>
<td>Significant differences were found between male and female teams in serve type, attack tempo and attack type; there was a predominance of ground serves, placed attacks and slower attack plays in women's volleyball, resulting in higher number of counterattacks.</td>
</tr>
<tr>
<td>2012</td>
<td>Chinchilla-Mira, Pérez-Turpin, Martínez-Carbonell, &amp; Jove-Tossi</td>
<td>Spatial analysis</td>
<td>659 actions</td>
<td>Comparing gender differences in beach volleyball, results showed men and women use different offensive zones and were different in the % of ball out. Differences were seen in points scored from zones 2 and 4, with the zone used more often by men for scoring.</td>
</tr>
<tr>
<td>2012</td>
<td>Lago-Ballesteros, Lago-Peñas, &amp; Rey</td>
<td>Technical/tactical</td>
<td>12 games</td>
<td>Of the 908 football possessions analysed, 303 (33.4%) produced a score box entry, 477 (52.5%) achieved progression and 128 (14.1%) failed to reach any sort of progression. Direct attacks and counterattacks were shown to be three times more effective than elaborate attacks in producing a score box possession. Possessions starting in the middle zones while playing against less than six defenders had greater success in reaching the score box compared to starting in the defensive zone with balanced defence. Game score had an effect, with a 43% and 53% reduction in probability of reaching the score box when the team is drawing or winning, respectively.</td>
</tr>
<tr>
<td>2012</td>
<td>Jörg M. Jäger &amp; Schöllhorn</td>
<td>Technical/tactical</td>
<td>120 actions</td>
<td>Base defensive position at the start of a game as well as the two players block with middle back deep at the end of a standard defensive situation are shown to be significantly different between national teams analysed. There are also significant differences between the national team's variability of the defence systems and start positions are more variable than the end positions.</td>
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</tbody>
</table>
### 2012

**Moura, Martins, Anido, De Barros, & Cunha**

**Spatial analysis**

- **8 games**

Team area and spread was analysed over time, and it was found that there was a significantly smaller team spread and team area on defence compared to offence. When defending teams conceded shots on goal there was a greater area and spread compared to when the teams performed tackles. Inversely, when a team created shots on goal on offence, the teams had a larger spread and area when they suffered tackles compared to when they had shots on goal.

### 2013

**Pulling, Robins, & Rixon**

**Technical/tactical**

- **50 games**

Analysis of defensive systems used during corner kicks in football showed that one-to-one marking was the most common system (90.1%) with zone marking being used 9.9% of the time. No significant difference was seen between the marking set-up and the number of shots on goal. Teams using a zone system conceded fewer goals and fewer attempts at goal relative to total attempts. Finally there was no significant difference between the positioning of defensive players at the goalposts and the number of shots on goal conceded when defending the corner kick.

### 2013

**Courel, Suarez, Ortega, Pinar, & Cardenas**

**Technical/tactical**

- **9 games**

In an analysis of the inside pass in basketball offence, it was shown that attacking possessions that involve an inside pass are more effective and achieve a larger amount of points; additionally, passer location and immediate receiver action determine the success of the inside pass, with the outside pass with an inside reception being most effective.

### 2013

**Gómez, Lorenzo, Ibañez, & Sampaio**

**Technical/tactical**

- **40 games**

In both genders, during the first five minutes, there were relations between ball possession effectiveness and number of passes and end player (player position). There were also relations shown with starting and ending zone and screens used during the middle 30 minutes. No relations were found in the last minutes of a game. Men's teams showed relations between effectiveness and screens used in the first five minutes; women's teams showed relations between effectiveness and starting and ending zone and defensive systems during the first five minutes.

### 2013

**Monteiro, Tavares, & Santos**

**Technical/tactical**

- **8 games**

Factors that characterise fast breaks in male and female basketball were investigated and showed that for female teams, the fast break was most often initiated by defensive rebounds in areas near the basket; for males it was through interceptions. For both groups fast breaks were most often
initiated with an outlet pass to the midcourt. Most common fast break situations was $1 \times 1$ followed by $1 \times 0$ and the lay-up was the most common way of finishing the possession. Males had a greater number and were more efficient at executing the fast break.

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Type/Style</th>
<th>Games</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>Gómez, Prieto, Pérez, &amp; Sampaio</td>
<td>Technical/tactical</td>
<td>14 games`</td>
<td>Analysis of ball possession effectiveness in floorball (similar to hockey) showed no interaction with the game period and effectiveness; In games with two high quality teams associations were seen with ending zone, offensive system, possession duration, height of shooting and defensive pressures previous to the shot. In games with one high quality team and one low, starting zone, possession duration, defensive pressure previous to a pass and to the shot, technique of shooting and the number of players involved in each possession was related to possession effectiveness. In low quality match ups results showed the importance of starting and ending zones, number of passes, and technique of shotting.</td>
</tr>
<tr>
<td>2013</td>
<td>Seweryniak, Mroczek, &amp; Łukasik</td>
<td>Technical/tactical</td>
<td>10 games</td>
<td>14 different defensive systems were identified, of those 4 accounted for 75% of the defensive actions. Of those, one system (only identified as system 2) was used 45% of the time and was the most effective.</td>
</tr>
<tr>
<td>2013</td>
<td>Wheeler, Mills, Lyons, &amp; Harrinton</td>
<td>Technical/tactical</td>
<td>60 games</td>
<td>Counter ruck (competing for the ball without hands) and jackal (competing for the ball with hands) were both found to be effective defensive tactics to turn over possession behind the advantage line in rugby union (60% and 39% turnovers, respectively). Early counter ruck was also effective in cases where the ruck contest was in the wide attack channels (18%) and a jackal was used in ruck contests in the central field areas (13%).</td>
</tr>
<tr>
<td>2013</td>
<td>Stankovic</td>
<td>Technical/tactical</td>
<td>7 games</td>
<td>Five general defensive variables, seven types of defence and six game variables were analysed. Results showed the team with the higher general defence efficiency was successful. Individual game reports consisting of specific defensive analyses are presented.</td>
</tr>
<tr>
<td>2013</td>
<td>Moura et al.</td>
<td>Spatial analysis</td>
<td>10 games</td>
<td>Team surface area and spread were analysed over time, showing that the surface area mean frequencies were significantly higher in the first half compared to the second. Similarly, spread median frequencies for the first half were significantly greater than the second half.</td>
</tr>
</tbody>
</table>
### Chapter 2 – Review of Literature

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Sample</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>Schrapf &amp; Tilp</td>
<td>Machine learning</td>
<td>6 games</td>
<td>Used ANN to classify similar action sequences (ball trajectories). 32 clusters were recognised, and 10 sequences could not be classified (meaning they were unique). 8 clusters represented 49% of all sequences and give good insight into the behaviours of the team used to create scoring opportunities.</td>
</tr>
<tr>
<td>2014</td>
<td>Wallace &amp; Norton</td>
<td>Retrospective</td>
<td>12 games</td>
<td>Variables related to game structure, speed and play patterns were analysed from FIFA World cup finals from 1966 to 2012. Play duration decreased, while stoppage time increased, affecting the work to rest ratio of players; game speed (measured from ball movements) increased by 15%; play structure moved towards a structure with high player density with a 35% higher passing rate.</td>
</tr>
<tr>
<td>2014</td>
<td>Silva, Garganta, Santos, &amp; Teoldo</td>
<td>Field Test</td>
<td>3482 actions</td>
<td>Results showed game play was less aggressive in 6 v 6 games compared to 3 v 3 games based on tactical variables analysed. This is the same conclusion drawn from Costa et al. (2010).</td>
</tr>
<tr>
<td>2014</td>
<td>Garcia, Román, Calleja-González, &amp; Dellal</td>
<td>Technical/tactical</td>
<td>50 games</td>
<td>5 v 5, 7 v 7 and 9 v 9 sided games from U/9 and U/14 football players were used to investigate offensive situations. Significant differences were seen in total number of touches per game and average number of touches per outfield player in 5 v 5 formats. Distribution of touches was similar for the different formats. Total scoring attempts, penalty area entries and attempted dribbles were also higher in 5 v5. Attempted passes were higher in both age groups for 5 v5 games.</td>
</tr>
<tr>
<td>2014</td>
<td>Graham &amp; Mayberry</td>
<td>Technical/tactical</td>
<td>45 games</td>
<td>According to the introduced statistic of 'efficiency rating', the direct shot is the most efficient strategy despite being employed far less than centre or perimeter tactics. Of 25 tactical variables, exclusion conversion rate is the most important discriminatory of winning teams in close and unbalanced games with 90% accuracy in classifying game results.</td>
</tr>
<tr>
<td>2014</td>
<td>Perica, Trninić, &amp; Jelaska</td>
<td>Technical/tactical</td>
<td>24 games</td>
<td>Results showed offence and defence are interrelated phases of play. Specifically, successful transition offence is closely linked with successful positional and transition defence. Conversely, unsuccessful transition offence is influenced by unsuccessful defence. Successful transition defence is determined by the success of the previous offensive phase.</td>
</tr>
</tbody>
</table>
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(meaning shot selection and offensive rebonding tactics are important for setting up transition defence).

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Sample Size</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>Travassos, Vilar, Araújo, &amp; McGarry</td>
<td>Dynamic systems theory</td>
<td>30 actions</td>
<td>4v4 and 4v3 small sided football games were analysed to understand if there is a change in tactical behaviour. Degree of coupling of players and teams were used to express tactical performance. Results showed stronger couplings in the defending dyads, defending player ball pairs and the defending team and ball for the unequal numbers game. There were also decreased distances between players to their team centroid, decreased surface areas and increased distances between team centroid were observed for unequal playing numbers.</td>
</tr>
<tr>
<td>2014</td>
<td>Leite et al.</td>
<td>Spatial analysis</td>
<td>1 game</td>
<td>All defensive systems showed a strong in-phase attraction in both lateral and longitudinal directions, team centroids were closer and had higher irregularity in lateral displacements. The FULL defence system increased distances of players to their own and oppositions team centroids; there was a gradual increase in player distance to team centroid in the closing moments of a quarter; distance of each player to each basket showed teams spent more time in defence and transition than offence.</td>
</tr>
<tr>
<td>2015</td>
<td>Barreira et al.</td>
<td>Retrospective/Tactical technical</td>
<td>45 games</td>
<td>Generalizability theory was used as the basis of the statistical analysis and showed patterns of play changed by 31.4% from 1982 to 2010. Match status influenced team dynamics, competition stage and game period. From 2002 to 2010 teams tended to use less ball dribbling and increased long passing rates; attacks down the wing increased over time. Dynamics have changed from individual work to more team work over the last 30 years.</td>
</tr>
<tr>
<td>2015</td>
<td>Clemente, Martins, Kalamaras, Wong, et al.</td>
<td>Network analysis</td>
<td>64 games</td>
<td>Significant differences were seen in the passing network metrics of network density and total links between the teams that reached the latter stages of the 2014 FIFA World Cup. Total links showed a small correlation with total links (r=0.24) and clustering coefficient (r=0.17). Concludes that high levels of connectivity between teammates are associated with better overall team performance.</td>
</tr>
<tr>
<td>Year</td>
<td>Authors</td>
<td>Type of Analysis</td>
<td>Games</td>
<td>Findings</td>
</tr>
<tr>
<td>------</td>
<td>--------------------</td>
<td>-------------------</td>
<td>-------</td>
<td>--------------------------------------------------------------------------</td>
</tr>
<tr>
<td>2015</td>
<td>Clemente et al.</td>
<td>Network analysis</td>
<td>4</td>
<td>Attack building was most influenced by defenders and midfields as measured with network metrics of degree centrality. Degree prestige showed midfielders were the main targets of the team to pass to in offence.</td>
</tr>
<tr>
<td>2015</td>
<td>Clemente, Martins, &amp; Mendes</td>
<td>Network analysis</td>
<td>6</td>
<td>No significant difference was found between different competitive levels in centrality measures. Position 3 was shown to receive the most passes, statistically different from position 1 and position 5 in balls received, from position 4 and 5 in passes for teammates and 5 in overall prominence. Position 5 had the lowest values of passes performed and overall prominence in the attacking dynamics.</td>
</tr>
<tr>
<td>2015</td>
<td>Gómez et al.</td>
<td>Technical/tactical</td>
<td>20</td>
<td>A number of variables were used to understand the most influential on screen success. The only time variable that showed significant change was the shot clock, with teams being more successful within the last 8 seconds of the shot clock. Orientation of the screen was significant, with lateral screens showing lower success in contrast to top screen and baseline screens. No player position related variables were significant.</td>
</tr>
<tr>
<td>2015</td>
<td>Olthof, Frencken, &amp; Lemmink</td>
<td>Spatial analysis</td>
<td>24</td>
<td>U/19 sample group showed significantly larger lateral stretch index and a significantly lower length per width ratio compared to the U/17 sample group. Both groups showed strong in-phase relations and similar variability in tactical performance measures.</td>
</tr>
</tbody>
</table>
CHAPTER 3.

Study 1: Playing unpredictably: Measuring the entropy of ball trajectories in international women’s basketball

Authorship Statement

Statement from co-authors confirming the authorship contribution of the PhD candidate

"As co-authors of the paper ‘Playing unpredictably: measuring the entropy of ball trajectories in international women’s basketball’ we confirm that Wade Hobbs has made the following contributions: Study concept, design, Data entry, data analysis, interpretation, and manuscript preparation."

In particular, the candidate’s contribution to the following items should be noted:

• conception and design of the research
• analysis and interpretation of the findings
• writing the paper and critical appraisal of content

Signed……………………………………………………………Date:

Signed……………………………………………………………Date:

Signed……………………………………………………………Date:

Signed……………………………………………………………Date:
3.1 Abstract

It is generally accepted that playing unpredictable basketball is advantageous, however this strategic assumption has not been adequately tested. The aim of this study was to describe unpredictability of in-play ball movement trajectories during a selection of women’s international basketball games to determine the association, if any, between unpredictability and success in basketball. Ball movements were tracked for 60 international women’s basketball games over a two-year period. Ball movements were broken into five second play segments and the spatial distribution of the ball was tracked across the court. Shannon’s entropy was then used to estimate the relative variability in ball movements. While no differences in entropy were observed between teams, the overall analysis revealed that entropy during large-deficit games (score differential of 10 points or more) was greater than that for small-deficit games and large-deficit wins showed greater entropy than large-deficit losses. Additionally, the entropy in the front court (the scoring end for a given team) was significantly greater for wins compared to losses. This suggests that higher entropy may be associated with success in basketball, but more specifically, entropy in the front court is potentially where it matters most.

3.2 Introduction

Basketball is a team-based invasion sport that requires competitors to operate in a highly dynamic and time-stressed environment. Strategy and tactics are critical to successful team outcomes. While related, strategy refers to the plan of how to win made ahead of time and modified to exploit weaknesses of the opposition, while tactics refer to in-game actions made in response to opposition actions which are reliant upon player’s skill (Gréhaigne, et al., 1999). A commonly utilised and critically important strategy within basketball is unpredictability. This strategy attempts to implement attacking sequences within the game
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that cannot easily be predicted by the opposition, making them harder to defend and leading to greater scoring opportunities (D’Amour, Cervone, Bornn, & Goldsberry, 2015). Despite its importance, few studies have attempted to measure the unpredictability of team collective behaviour in basketball (i.e., emergent behaviours within a team, encompassing team strategy and tactics).

One study to date has described the unpredictability of offensive performance in basketball. In this study, entropy (a measure of unpredictability) was calculated for National Basketball Association (NBA) players and their corresponding ball movements (D’Amour, et al., 2015). In the study, higher entropy denoted greater unpredictability. The study showed a significant relationship between entropy and the probability of an open shot, such that teams who were less predictable had a greater chance of creating a situation in which an attacking player was undefended in a high percentage shooting area. Intuitively, a negative correlation was also observed between entropy and immediate opportunity, such that unpredictability was significantly reduced during moments in which the ball-carrier was in a high percentage shooting situation. While this study was the first to identify associations between entropy and key outcomes in basketball, it utilised highly advanced and prohibitively expensive optical tracking systems that are not widely available. Specifically, this system utilises multiple cameras surrounding a court to track the movement of both players and ball location automatically with specialised software. While this technology is used in the NBA and recently in the 2017 Euroleague Final competition, it is not available for the vast majority of competitions, including international competitions such as the Olympic Games. Furthermore, the analysis of these data requires inordinately large datasets consisting of hundreds of games in order to train statistical models, which are unattainable in international basketball due to the relatively small number of games played at this level in any given year. Consequently, the
development of alternative methods to measure unpredictability are required to enhance our understanding of its role in team success in other basketball contexts.

While not yet applied to basketball, Lucey et al. (2012) developed a novel entropy measurement method in soccer/football using readily available video-based technology. In this study, ball location data from 380 English Premier League football matches were used to characterise team behaviour. The field was segmented into a 20 x 16 grid and entropy was calculated for each cell in the grid, resulting in entropy heat maps capable of highlighting individual team characteristics. This study showed that higher entropy values were displayed by the top five ranked teams and provides a framework for measuring entropy when more sophisticated methods are not available. Applied to basketball, this entropy measurement method has potential to greatly enhance our understanding of the role of entropy within contexts outside of the NBA, which may shape the way strategy is developed and implemented in Olympic and International contexts.

Therefore, the aim of this study was to describe ball trajectory entropy during a selection of women’s international basketball games to determine the association, if any, between entropy and success in this basketball context. We hypothesised that more successful teams would play with higher entropy, and that entropy during games won would be higher than that during games lost.

### 3.3 Methods

#### 3.3.1 Data collection

The study was reviewed by the University of Sydney Research Integrity and Ethics Administration and deemed to be exempt from a human ethics review. Ball trajectories from
60 international women’s basketball games (6 teams and 10 games each) were manually notated from video recordings using the bespoke software, ‘Pattern Plotter’ (Morgan, 2007). Due to the low number of international women’s competitions, games were collected from a range of sources across three years of competition, with 32 games from the 2016 Rio Olympic Games, 10 friendly games, 8 from the 2015 Olympic qualifying tournament, 5 from the 2015 Eurobasket competition, 4 from the 2014 FIBA World Championships and 2 from the 2015 FIBA Asia Women’s Championship. The six teams chosen for analysis consisted of Australia, Belarus, France, Japan, Turkey and the United States of America (USA). Team selection was a strategic decision aligned with the interests of the Australian Women’s Basketball team’s coaching staff for the 2016 Olympic Games, as Australia, Belarus, France, Japan and Turkey were all allocated to Pool A, whereas the USA were the current world and Olympic champions. The sixth team in Pool A, Brazil, was omitted because ten games under the same coach could not be sourced.

For each game, the ball path of all possessions which ended in a shot (either successful or unsuccessful) were determined via manual tracking to yield x- and y-coordinate data over time. Specifically, video footage (Fig 1 D) was used to estimate ball location on a virtual court (Fig 1 C) with a code window (Fig 1 B) allowing metadata to also be encoded (e.g., shot, turnover, foul). These data were stored in a log during the tracking process (Fig 1 A) and were then exported for analysis (Table 1).
Table 1. Example of exported data for analysis.

<table>
<thead>
<tr>
<th>GameID</th>
<th>TimeCriteria</th>
<th>TeamName</th>
<th>RecordID</th>
<th>Time</th>
<th>x</th>
<th>y</th>
<th>Label1</th>
<th>Label2</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>62</td>
<td>42</td>
<td>63</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>63</td>
<td>47</td>
<td>51</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>64</td>
<td>50</td>
<td>28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>65</td>
<td>45</td>
<td>45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>66</td>
<td>35</td>
<td>46</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>66</td>
<td>32</td>
<td>46</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>67</td>
<td>22</td>
<td>37</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>69</td>
<td>35</td>
<td>22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>71</td>
<td>45</td>
<td>31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>71</td>
<td>44</td>
<td>35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>72</td>
<td>38</td>
<td>40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>73</td>
<td>34</td>
<td>43</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>74</td>
<td>52</td>
<td>17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUS v SRB</td>
<td>1st Quarter</td>
<td>AUS</td>
<td>2</td>
<td>76</td>
<td>36</td>
<td>19</td>
<td>Shot</td>
<td>Score</td>
</tr>
</tbody>
</table>
3.3.2 Data preparation

Entropy calculations require regular time-series data however, the manual tracking procedure produces data at irregular time intervals due to variations in the time of game events. Consequently, x- and y-values were interpolated between regular time points by applying a smooth spline function to each possession to achieve temporally-equispaced coordinate data. This applied separate cubic smoothing functions for both the x- and y-locations, as well as for the time data, allowing for the manipulation of sampling rate, such that x and y data points could be generated as many times per second as required. The shape of the trajectories for the actual and interpolated data were closely matched as shown in Fig. 2. The x- and y-coordinates were then converted into a single location value by taking the coordinates of the ball for each second of the trajectory and transforming them into a corresponding cell. For example, as shown in Fig 3, if the ball was at x = 16 and y = 55 the corresponding cell would be 22. This transformation was performed over the full possession, producing a vector of cell identification numbers (cell IDs) (see Fig 3 top right) and time values for each possession.
Figure 2. Plot showing the raw data (circles) and the piecewise polynomial model (solid line) for x location and time data points.

Possessions lasting less than 4 s were excluded from analysis, as the smooth spline function requires at least four unique time values. This equated to approximately 10% of the total possessions for a team and generally consisted of an in-bound pass followed by an immediate shot which have little strategic value in the context of the present study.
Figure 3. A typical ball trajectory shown on court (dashed lines represent a pass, solid lines represent dribbling the ball) lasting for 15 s and ending in a shot. Each ball trajectory is converted to a vector of cell IDs (top right) and segments into 5 s play segments.

To account for the varying length in time of possessions, the cell ID vector was segmented into five second ‘play-segments’. A sliding window of 5s then incremented along the cell ID vector each second (Fig 3) until it reached the end of the possession. The resulting 5s play segments were used to fill frequency distributions over all cells (Fig 4) (Lucey, et al., 2012). The frequency distributions contain a count of how many times the ball passed through each cell from a given starting cell. For example, the possession in Fig 3 starts in cell 47, the frequency distribution for cell 47 will show a count of 1 for cell’s 42, 37, 31 and 26, the sliding window then moves along 1s and counts each cell the ball passed through for cell 42 (which were 37, 31, 26 and 22). This process was repeated for each possession of each game, resulting in distributions showing the spread of ball movements for each cell.
3.3.3 Entropy calculation

Shannon’s entropy was calculated from the frequency distributions using the maximum likelihood estimate (Hausser and Strimmer, 2009). This measure describes the likelihood of the ball entering any of the 50 cells across the court. For example, if the ball started in cell 50 (bottom right cell seen in Fig 3) and entered each of the other remaining 49 cells an equal number of times, this would result in maximum entropy as the ball is equally likely to enter any other cell, and therefore the movement of the ball is highly unpredictable. If the ball moved from cell 50 to cell 45 each time it was measured, this would result in minimum entropy, as the ball movement is highly predictable. The minimum entropy value is 0. The maximum entropy value is based on the number of categories included in the calculation, with more categories (or cells in this case) resulting in more uncertainty of the result. In this
case the maximum is 3.91. Finally, entropy increases with the amount of data used in its calculation, therefore when comparing the entropy of teams or conditions, it is necessary to ensure entropy is calculated using the same number of games for each team or condition.

### 3.3.4 Reliability

Reliability of entropy values was tested by re-tracking a randomly-selected game. This created approximately 1100 data points for comparison and generated an intra-class correlation coefficient of .73 and standard error of measurement (SEM) 0.0096, suggesting a high level of measurement reliability. This increased substantially (ICC = .88) with the removal of cells containing fewer than ten counts (Fig 5). In these low count cells, a mismatch of possession counts led to wider variations in entropy compared to cells with high possession counts. Cells with fewer than ten counts (cells 46 and 50 in Fig 5) were therefore removed from analysis. All other cells satisfied the condition of having greater than ten counts.
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Figure 5. Plot showing entropy scores for each cell for the same game tracked twice. Highlighted outliers indicate cells with fewer than 10 ball trajectory counts, leading to low reliability.

Several temporal and spatial conditions were compared before finalising the current set of conditions. Spatially, a relationship between reliability and granularity was found (granularity here relates to the size of cells, in that smaller cells denote a finer granularity of the measure). Due to data being collected manually, increasing granularity by reducing cell size resulted in a decrease in reliability. Consequently, a 4 x 8 grid and a 5 x 10 grid were tested to find an acceptable balance of these two variables. The intra-class correlation reliability of a 4 x 8 grid was 0.79 and 0.94 when four outliers were excluded, compared to 0.73 and 0.88 when 4 outliers were excluded for a 5 x 10 grid. To maximise granularity while maintaining acceptable reliability, the 5 x 10 grid was chosen. Sampling rates (the time interval at which x- and y-locations of the ball were sampled) of 1 s, 0.5 s, and 0.2 s were also tested, showing that increasing sample rate decreased reliability (Table 2). The choice of a sampling rate of 1 s was made based on these results to maximise reliability.

Table 2. Reliability (ICC) measures for sampling rates at 1 s, 0.5 s, and 0.2 s, tested on a 5 x 10 grid and 4 x 8 grid.

<table>
<thead>
<tr>
<th>Sampling rate (s)</th>
<th>5x10</th>
<th>4x8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.731</td>
<td>0.659</td>
</tr>
<tr>
<td>0.5</td>
<td>0.608</td>
<td>0.611</td>
</tr>
<tr>
<td>0.2</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.792</td>
<td>0.659</td>
</tr>
<tr>
<td>0.5</td>
<td></td>
<td>0.611</td>
</tr>
<tr>
<td>0.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.3.5 Data analysis

Entropy values for each cell for each team were compared using a one-way ANOVA and effect size was calculated using partial eta squared. Furthermore, entropy values were calculated for each cell from all won games and all lost games, large-deficit and small-deficit
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games (point differential greater or less than 10 points, respectively), and variations of the
two (large-deficit games won versus large-deficit games lost; small-deficit games won versus
small-deficit games lost). These conditions were tested for differences using paired samples t-
tests and effect size was calculated using Cohen’s d. Finally, entropy was calculated from a
pooled dataset of all 60 games for quarter 1, 2, 3, and 4 separately to test if entropy changed
through the course of a game.

In addition to the full court entropy analyses, a sub-analysis was conducted for entropy of
front court cells only. The rationale for this was two-fold: firstly, in the game of basketball,
the majority of possessions are characterised by an individual offensive player carrying the
ball forward through the back court without defensive pressure. This significantly reduces the
strategic significance of entropy within the back-court region. For many coaches, strategy
(and indeed unpredictability) is only of relevance in the front court. Secondly, the rules of the
game of basketball dictate that the ball cannot pass into to the backcourt once it has passed
into the front court. Therefore, fewer possibilities exist for ball movement within the front
court compared with the backcourt, making the scale of entropy values lower in the front
court compared with the back court.

Given that entropy increases with sample size, all comparisons require an equal number of
games. This did not affect the primary outcome of team effect, as each team’s entropy was
calculated from 10 games of data. However, the number of games won was greater than
games lost in the current sample (34 vs 26 respectively), and large-deficit wins were greater
than large-deficit losses (21 vs 13 respectively). This mismatch was a result of only tracking
the ball for one team in a select few games to reach the target of ten games per team.
Consequently, a bootstrapping method was implemented such that games in the larger
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condition (wins and large-deficit wins) were randomly selected from the pool and used to calculate entropy. This was repeated five times and the mean of the repeated samples was taken as the data set for comparison.

3.4 Results

No significant team effect for entropy was observed, \( F(1, 5) = 0.75, p = .66, \eta^2 = .01 \) (Fig 6), and no difference in entropy was observed for won and lost games \( (2.82 \pm .19 \text{ vs } 2.80 \pm .22, p = .1, d = .24, \text{CI} = -0.004, 0.05) \). Results were considered statistically significant if alpha was less than 0.05. Partial Eta-squared was considered small for values of .01 to .06, medium for .06 to .14 and large for > .14. Cohen’s d was considered small for values of .2 to .5, medium for .5 to .8, large for > .8.

Figure 6. Heat map showing how entropy varies across the court. Ball movement for the attacking team moves from the bottom to the top of the court.

Entropy during large-deficit games however, was significantly higher than entropy during small-deficit games \( (2.83 \pm .21 \text{ vs } 2.79 \pm .19, p = .002, d = -0.46, \text{CI} = 0.014, 0.058) \) and large-deficit wins had greater entropy than large-deficit losses \( (2.80 \pm .19 \text{ vs } 2.76 \pm .22, p = .004, d = 0.43, \text{CI} = 0.014, 0.071) \). Entropy was not significantly different between small-
deficit wins and small-deficit losses (2.71 ± .17 vs 2.75 ± .21, \( p = .06, d = -0.27, CI = -0.08, 0.002 \)) (Table 3). This indicates a potential association between moving the ball with high unpredictability and success in basketball. The lower entropy observed in close games compared with large-deficit games, may be a predetermined tactic, with the coach prescribing specific offensive plays, or it could simply be an emergent feature of team sport gameplay with teams going to a smaller number of successful plays instead of playing unpredictably.

Table 3. Mean entropy values for won, lost, large-deficit win, large-deficit loss, small-deficit win, and small-deficit loss, separated into full court and front court results. Direct comparisons can be made between conditions with matching number of games. a Denotes a significant result.

<table>
<thead>
<tr>
<th></th>
<th>Win</th>
<th>Loss</th>
<th>Large-deficit win</th>
<th>Large-deficit loss</th>
<th>Small-deficit win</th>
<th>Small-deficit loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Court</td>
<td>2.82 ± .19</td>
<td>2.80 ± .22</td>
<td>2.80 ± .19</td>
<td>2.76 ± .22*</td>
<td>2.71 ± .17</td>
<td>2.75 ± .21</td>
</tr>
<tr>
<td>Front Court</td>
<td>2.67 ± .06</td>
<td>2.62 ± .09*</td>
<td>2.65 ± .07</td>
<td>2.60 ± .1*</td>
<td>2.62 ± .08</td>
<td>2.59 ± .1</td>
</tr>
<tr>
<td>No. of games</td>
<td>26</td>
<td>26</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>13</td>
</tr>
</tbody>
</table>

Entropy was significantly higher in the back court compared with the front court (\( d = 1.8, p = > .001, CI = 0.4, 0.26 \)) (see Fig 6). While potentially this represents greater unpredictability in the back court, we attribute this finding to the rules of the game which forbid the ball to pass into the back court once it has crossed into the front court. This reduces the number of available cells for the ball to enter once in the front court, thereby reducing the potential entropy (Fig 4). This highlights the importance of front court analysis in isolation from the backcourt, as the larger entropy potential in the backcourt may mask relevant findings in the front court when analysed together.
Chapter 3 – Study 1

There were no significant differences found between quarters \((F (1, 3) = 0.77, p = .97, \eta^2 = .001\) or between the first and second halves \((2.81 \pm .21 \text{ vs } 2.80 \pm .21, p = .3, d = -0.27, CI = -0.01, 0.04)\)

3.4.1 Front court sub-analysis

Front court entropy was significantly greater in games won compared to games lost \((2.67 \pm .06 \text{ vs } 2.62 \pm .09, p = <.001, d = -0.67, CI = -0.08, -0.02)\), and large-deficit wins compared with large-deficit losses \((2.65 \pm .07 \text{ vs } 2.6 \pm .1, p = 0.01, d = -0.64, CI = 0.01, 0.098)\). No difference was observed between small-deficit wins and small-deficit losses \((2.62 \pm .08 \text{ vs } 2.59 \pm .1, p = .06, d = -0.36, CI = -0.002, 0.07)\). Entropy was greater during large-deficit games compared with small-deficit games \((2.64 \pm .08 \text{ vs } 2.66 \pm .07, p = .054, d = -0.28, CI = -0.04, 0.0004)\) (Fig 7).

Front court entropy results were similar to those of the full court however, games won showed significantly higher entropy compared to games lost. This suggests that higher entropy is associated with success in basketball, but more specifically, that entropy in the front court is potentially where this matters most. Furthermore, the front court results reveal a trend between winning margin and entropy, such that large-deficit wins had the highest entropy, followed by small-deficit wins, with losses of any margin showing similarly low entropy (Table 3).
3.5 Discussion

This is the first study to describe entropy for ball movement during international women’s basketball. While no between-team differences in entropy were observed, entropy was greater during large-deficit games than small-deficit games, and large-deficit wins had greater entropy than large-deficit losses. This suggests that entropy is associated more with the outcome of the game than specific features of a given team.

The findings suggest that unpredictability is an important feature of women’s international basketball. While reverse causality cannot be ruled out (the deficit influences the degree of entropy), these results indicate that entropy may be a critical determining factor of team success. That is, a high degree of entropy may lead to higher deficits, or simply be the result of less structured play during games of high deficit.
The results of the current study build upon a growing body of evidence that suggests entropy is a key strategy associated with successful performance in team sports. Our findings support those of Lucey et al. (2012) who showed the five highest ranked football teams in the English Premier League had the highest ball movement entropy. D’Amour et al. (2015) showed higher entropy led to more open shots which was a trait seen in the higher-ranked teams. Fewell et al. (2012) measured, among other metrics, the entropy of passing networks in basketball. Shannon’s entropy was applied to passing sequences across 16 games (two games each for eight teams in the NBA playoffs). Results showed the winning team from 6 of the 8 first round match-ups had higher team entropy. Furthermore, Skinner (2010) suggested there is a theoretical advantage to playing with higher variability based on game theory. Evidence is presented on traffic networks with game theory suggesting the way to decrease travel times for all is by some sacrificing the fastest route to reduce congestion. It is argued the same principles apply to basketball. The effectiveness of a tactic will see diminishing returns if it is used too often, as it will become predictable. Similarly, Skinner and Goldman (2015) suggest a basketball play is a function where the expected return (points scored) decreases with increased use. The “usage curve” function is defined as \( f(p) \) where \( f \) refers to the average number of points scored per possession when a particular play is run, and \( p \) is a fraction that represents the number of times that the play is used. Therefore, there is an optimal number of times a play can be run before there is a decline in the expected return. Broadly, these studies support the notion that entropy is an important factor in winning basketball games.

The ability to measure entropy from readily available technology could lead to valuable and actionable insights for international basketball teams and could be implemented with greater frequency. In general terms, teams should seek to increase the unpredictability of their play. Beyond this however, specific information can be gathered to inform both offensive and
defensive strategies. For example, within the current study, the USA entropy profile reveals highly predictable behaviour when the ball is in the corners of the front-court, potentially making them easier to defend when in this court location. This strategic information can inform offensive strategy for the USA to increase entropy from these specific locations, or to inform defensive strategy of their opponents to funnel the USA into these more predictable locations on the court. Conversely, Japan move the ball with high unpredictability in the key; strategically an opposing coach may focus greater defensive pressure in the key when playing against Japan (Fig 6).

Future research should continue to describe entropy using this technique to further the understanding of its role in team success. With continued technological advancement of tracking methods, this methodology can be developed to increase its accuracy and efficiency allowing more data to be collected with more precision. While this analysis of unpredictability does not try to predict what will happen next, it does provide insights into the variability of ball movements which may shed light on a team’s strategy and tactics. Furthermore, international basketball, and particularly the women’s game, is under-represented in sports science research despite being an Olympic sport. This may be due to the low number of games, making long term analysis of tactics and strategy difficult. The use of ball movement data helps overcome this limitation. However, a larger dataset may make it possible to answer questions such as the influence of defence on opposition entropy and whether entropy is a by-product of good team offence, or whether these teams simply seek to play unpredictably to improve performance.

Entropy of ball movements in basketball has been shown to provide insight into the dynamics of basketball while adding evidence to the association between unpredictability and success.
Chapter 3 – Study 1

in team sport. These finding are stimulus for future research and support the use of ball tracking within international basketball, and other team sports, for strategic purposes.
Chapter 3 – Study 1

3.6 References


Morgan, S. Pattern Plotter (Version 4.5x) [Computer Software]. Australian Institute of Sport.


CHAPTER 4.

Study 2: Measuring spatial scoring effectiveness in women’s basketball at the 2016 Olympic Games

Authorship Statement

Statement from co-authors confirming the authorship contribution of the PhD candidate

"As co-authors of the paper ‘Measuring spatial scoring effectiveness in women’s basketball at the 2016 Olympic Games’ we confirm that Wade Hobbs has made the following contributions: *Study concept, design, Data entry, data analysis, interpretation, and manuscript preparation.*"

In particular, the candidate’s contribution to the following items should be noted:

- conception and design of the research
- analysis and interpretation of the findings
- writing the paper and critical appraisal of content

Signed………………………………………………………………Date:

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Chapter 4 – Study 2

4.1 Abstract

Basketball strategy is often focused on how to use space on the court. However, very little research has investigated performance from a spatial perspective beyond the now ubiquitous shooting heat maps. The aim of this study was to quantify how effectively teams move the ball across the basketball court and identify the most commonly occurring sequences of ball movement in international women’s basketball. The results of the spatial analysis characterised trends in team play from the women’s 2016 Olympic basketball competition and demonstrated that overall, the right-hand side under the basket and the top-right 3-point area were the most effective areas on the court. In general terms, the right-hand side of the court was more effective than the left, and the middle of the court was more effective than the wings. Of the teams included in the study, the United States of America demonstrated the greatest overall effectiveness. Finally, the most commonly occurring ball movement sequences were identified with five of the seven teams demonstrating the same pattern. The quantification of spatial effectiveness in the current study provides insight into the specific tendencies of different teams and the areas that lead to the most effective outcomes. Coaches can apply this information to devise game plans aimed at counteracting the specific tendencies of opposing teams.

4.2 Introduction

Performance analysis in basketball has identified a number of key performance variables that are critical to success. High shooting percentage, low turnover rates, and a high number of offensive rebounds and free throws have been associated with winning games (Oliver, 2004). Consequently, basketball analysis has commonly involved analysing the frequency of these variables to gain insight into strategies that might lead to greater probabilities of winning. This includes the ubiquitous box-score information which includes a breakdown of shooting
performance, rebounds, turnovers, and assists for each individual player, as well as more specific variables such as offensive tactics, defensive tactics, and shooting locations. This approach has been criticised for neglecting the inherent complexities and interconnectedness of the environment, and for providing only limited, if any, contextual information that might help explain the causal mechanisms of these events (Garganta, 2009; Mackenzie and Cushion, 2013; McGarry, 2009). While the analysis of performance variables continues to provide some value, new methods are emerging which may provide greater contextual feedback to coaches regarding not only their own team’s performance, but also insight into the strategy of the opposition team.

A number of different approaches have been used to provide contextual information in basketball including Expected Possession Value (EPV) and Voronoi Diagrams (VD). Expected Possession Value quantifies the probability of scoring throughout a possession by fitting a probabilistic model to player tracking data to determine how decision-making is influenced by the spatial configuration of other players on the court. A point value is assigned for each moment in the possession, allowing for an evaluation of how decision-making effects the EPV (Cervone, D’Amour, Bornn, & Goldsberry, 2014). While this is a powerful tool to analyse basketball decision-making, to date, no studies have used this method to quantify a team’s effectiveness and how it changes as a function of court location. Voronoi Diagrams on the other hand identify the areas of most value on the court by quantifying how much space each player ‘controls’ at any moment in time (Cervone, Bornn, & Goldsberry, 2016). Higher value regions are identified by player movements and actions, indicating the most sought-after areas. Team specific court value plots can be created, showing how different teams value space on the court, giving insight into the strategy employed. This allows for clear visualisation of how different teams value space on the court, as well as
providing a ranking of both players’ and teams’ capability to open and close space, however, it does not allow associations to be drawn between these metrics and performance.

Spatial analysis that has attempted to determine associations with performance in basketball has primarily been confined to shooting performance. For example, spatial statistics applied to shooting maps found that during the 2006-2007 and 2008-2009 National Basketball Association (NBA) seasons, the Los Angeles Lakers differed significantly from the NBA average, shooting less shots in the key. Furthermore, clusters of shot attempts by the Los Angeles Lakers that were statistically higher or lower in incidence from the league average were presented (López Hernández, Martínez, & Ruiz Marín, 2013). This study, and others analysing spatial aspects of shooting (Goldsberry, 2012; Reich, Hodges, Carlin, & Reich, 2006; Shortridge, Goldsberry, & Adams, 2014), are important to understand the specific locations from where teams and players shoot, however it provides no information about where the play developed or how the shot attempt was initially created. While shooting efficiency has been identified as an important aspect of winning, and shooting has been analysed in great detail, more focus needs to be given to how teams create shooting opportunities.

Few studies outside of shooting analyses have attempted to link spatial information with performance outcomes and none have sought to do this in basketball. Stöckl and Morgan (2013) evaluated team spatial performance in women’s field hockey by mapping the likelihood of a goal shot occurring for each sector across the field. This study provided valuable information relating not only to where shots were taken, but also how they likely developed, however, no information was provided on the success of the shots on goal. This may have been due to the low-scoring nature of hockey (making shots on goal, rather than the
goals themselves, a more valid measure). This type of approach, that combines contextual information with performance outcomes, may prove to be valuable in basketball.

The current study therefore aimed to (1) develop a method to describe spatial effectiveness within basketball, (2) describe the relationship between effectiveness and court location among seven women’s international basketball teams during the 2016 Olympic Games, and (3) describe the most frequent ball-movement sequences for each team. In doing so, the aim was to provide a valuable tool for coaching staff to better understand their own team’s performance execution, as well as the strategy of the opposing team, and to develop both offensive and defensive strategies to optimise team effectiveness while simultaneously reducing the effectiveness of the opposition.

4.3 Methods

The study was reviewed by the University of Sydney Research Integrity and Ethics Administration and deemed to be exempt from a human ethics review. Ball trajectories were extracted from video recordings of the 2016 Olympic Games women’s basketball tournament using custom-designed software, ‘Pattern Plotter’ (Morgan, 2007). All group and finals games were tracked for the six teams in Group A as well as all games for the United States of America (USA) from Group B providing a balanced design as each team played every other team (with the exception of the USA). Group A consisted of Australia (AUS), Belarus (BLR), Brazil (BRA), France (FRA), Japan (JPN), and Turkey (TUR). Team selection was a strategic decision aligned with the interests of the Australian Women’s Basketball team’s coaching staff for the 2016 Olympic Games as Australia were to play each team in Group A, while the USA were the current world and Olympic champions.
Chapter 4 – Study 2

For each game, the ball path of all possessions was determined via manual tracking to yield x- and y-coordinate data over time. Specifically, video footage (Fig. 1 D) was used to estimate ball location on a virtual court (Fig. 1 C) with a code window (Fig. 1 B) allowing metadata to also be encoded (e.g., shot, turnover, foul). These data were stored in a log during the tracking process (Fig. 1 A) and were subsequently exported for analysis.

Figure 1. A. Tracking log; B. Coding window; C. Virtual Court, D. Video footage

4.3.1 Data preparation

The front-court was divided into a 4 x 4 grid (3.6 m x 3.8 m cells) with each cell assigned a number (see Fig. 2) increasing from left to right across the row. The raw x- and y-coordinates of the ball throughout the possession were transformed into the corresponding cell locations. For example, if the ball was at x = 40 and y = 21, the corresponding cell would be 12 (Fig. 2). This transformation was performed over the duration of each possession, starting from when the ball crossed the halfway line, as ball movements in the back-court have less relevance to possession outcomes for the majority of possessions. This produced a vector of cell identification numbers (cell IDs) and time values for each possession. With effectiveness as the primary outcome, any possession that did not result in a shot or change in possession was removed from the analysis (e.g., non-shooting foul or stoppage). Cells were attributed a score
of 1 for each possession that passed through that cell and ended in a positive outcome, and zero for each possession ending in a negative outcome. The total number of possessions for a given cell were also counted. Positive outcomes were defined as possessions ending in a score or shooting foul, and negative outcomes were defined as possessions ending in a missed shot or turnover. While a more robust definition of positive outcomes would be useful, such as classifying a shot as an open shot or pressured shot as in Lucey, Bialkowski, Carr, et al. (2014), without player locations to determine distance between the shooter and defender, this was not possible. Furthermore, in practice, whether the shot was made or not is typically the most critical information for coaches.

Figure 2. A typical ball trajectory shown on court.

4.3.2 Quantifying effectiveness

Associations between cell IDs and an outcome were determined through association rule mining, describing each cell by the frequency and likelihood of a given outcome (Stöckl and Morgan, 2013). Specifically, we tested the association between the ball passing through a
given cell and the outcome of the possession (positive or negative outcome) for each team. Association rule mining describes this as ‘confidence’, representing the conditional probability of a positive outcome given the specified cell,

\[
\text{Confidence (i)} = \frac{\text{Number of positive outcome events involving cell (i)}}{\text{Number of possessions involving cell (i)}}
\]

4.3.3 Confidence vs Usage

It is important to consider the relationship between confidence and usage (how often the ball passed through a cell during the game). Confidence is the percentage of positive outcomes for a given cell divided by total possessions for that cell, however the number of possessions used for each calculation can vary widely. A cell with high usage can have the same confidence as a low usage cell: the proportions are the same, but their explanatory power is not.

Given that two cells of similar confidence but different usage frequencies have significantly different effectiveness implications, a standardisation calculation was applied to all cells to allow fair comparisons to be made between cells. Specifically, the proportion was divided by the approximated standard deviation of the proportion using the equation (1) below where SE = standardised effectiveness, \( p \) = proportion and \( n \) = the count of possessions:

\[
SE = \frac{p}{\sqrt{\frac{p(1-p)}{n}}}
\]

(1)

The result is a scaled number based on usage and confidence to provide a standardised effectiveness value. While this value is arbitrary and has no intuitive interpretation and is only comparable to other standardised values, it better represents team spatial effectiveness.
4.3.4 Sequence analysis

Data from all group games were combined for each team and searched for the most commonly occurring sub-sequences. This was achieved by searching for ‘\( n \)-grams’. Typically used in probabilistic language data mining to predict the next word in a sentence, a sequence is searched for \( n \) items (or grams) in a larger sequence. In this case, the larger sequence of all cell IDs was searched for commonly occurring sub-sequences between 3 and 4 cell IDs in length. Longer sequences were not included because there were not enough data to find meaningful results. A list of 3- and 4-grams of varying frequency were found for each team. This analysis was conditioned on the most effective cell for each team, producing a list of the most common ball paths through each team’s most effective cell.

4.3.5 Reliability

Reliability of standardised effectiveness values was tested by randomly selecting and re-tracking a game to produce a second set of ball tracking data. Test-retest reliability of the standardised effectiveness values were measured by intra-class correlation resulting in a coefficient of .88 showing ‘good’ reliability of measures. Paired \( t \)-tests were carried out to test for bias in the data, the results of which were not significant (\( p = .55, \text{CI} = -0.23, 0.41 \)). The standard error of measurement was .43. Finally, Bland Altman limits of agreement were \( \pm 1.16 \).

4.3.6 Standardise effectiveness z-scores

A high degree of spatial similarity was identified between teams for effectiveness such that most teams had high effectiveness in the front-centre of the court and lower effectiveness in
the corners and edges of the court (Fig. 3). Therefore, games and teams were compared spatially by calculating the z-score for each cell over five group games for each team. This allowed for descriptive comparisons of performance across the court, identifying a given team’s spatial strengths and weaknesses.

4.3.7 Defensive effectiveness

Mean defensive effectiveness was quantified for each team by taking the average offensive effectiveness of opponents for each team. For example, a team’s mean defensive effectiveness is the average of all their opponents standardised effectiveness across the tournament.

4.3.8 Statistical analysis

Standardised effectiveness values between and within teams across group games were compared using a one-way ANOVA and effect sizes using partial eta squared. Two of the seven teams did not make it past the group stage of the tournament, therefore, to ensure that the comparisons were balanced, only group games (rather than finals) were used to compare mean effectiveness between and within teams. To evaluate the capability of effectiveness to explain game results, mean game effectiveness was compared to actual game outcomes (win or loss) and the difference between team’s mean standardised effectiveness was correlated with the point differential for the game.

4.4 Results

Overall mean standardised effectiveness for all cells was 4.11 ± 1.26 (Appendix A). Cell 11 had the highest mean standardised effectiveness (5.51), followed by cell 3 (5.16), cell 7, and
cell 10 (5.02). Cell 3 was the most effective area for Australia, Brazil, France, and the USA; cell 11 was most effective for Japan and Turkey; and cell 7 was the most effective cell for Belarus (Fig. 3).

Figure 3. Heat maps of standardised effectiveness results for each team.

To highlight spatial effectiveness for each team relative to the overall average, heat maps were generated using the z-score to show whether a team was above or below the combined average for each cell (Fig. 4). While these maps are purely descriptive, they provide an indication of a team’s strengths and weaknesses which may be useful to coaches when developing their game strategy.
Figure 4. Z-score heat maps of standardised effectiveness for each team across all group games. Green indicates above average standardised effectiveness and red indicates below average.

To further examine the results, the sixteen cells were grouped into strategically important areas of the court including the post and key area (cells 2, 3, 6, and 7), the corners (cells 1 and 4), the wings (cells 5, 8, 9, and 12), and the top of the key (cells 10 and 11) (Table 1). This summarised grouping of cells provides a more intuitive and easily communicated way to present the results, which would be of particular interest to coaches.

Table 1. Summary of effectiveness z-scores for strategically important areas for each team.

<table>
<thead>
<tr>
<th></th>
<th>AUS</th>
<th>BLR</th>
<th>BRA</th>
<th>FRA</th>
<th>JPN</th>
<th>TUR</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Key</td>
<td>0.20</td>
<td>-0.26</td>
<td>-0.98</td>
<td>-0.47</td>
<td>0.34</td>
<td>-0.58</td>
<td>1.75</td>
</tr>
<tr>
<td>Corner</td>
<td>0.73</td>
<td>-0.74</td>
<td>0.22</td>
<td>0.74</td>
<td>-0.33</td>
<td>0.06</td>
<td>-0.68</td>
</tr>
<tr>
<td>Wing</td>
<td>-0.22</td>
<td>0.30</td>
<td>-1.25</td>
<td>-0.32</td>
<td>-0.21</td>
<td>0.15</td>
<td>1.54</td>
</tr>
<tr>
<td>Top of key</td>
<td>0.04</td>
<td>-0.56</td>
<td>-0.90</td>
<td>-0.56</td>
<td>0.41</td>
<td>-0.26</td>
<td>1.83</td>
</tr>
</tbody>
</table>

Results of the defensive effectiveness analysis showed a similar pattern seen in offensive effectiveness, with higher effectiveness in the key and top of the key areas. However, noticeable differences can be seen between teams (Fig. 5). Low defensive effectiveness
indicated a positive defensive performance. Turkey had the lowest defensive effectiveness, while Brazil had the highest defensive effectiveness.

Figure 5. Heat maps of mean defensive effectiveness across 5 group games. Green indicates a higher standardised effectiveness value which in regard to defensive effectiveness, is a negative attribute.

The sequence analysis showed Australia, France, Belarus, and Turkey’s most common sequence of ball movements were from the left-top of the key (cell 10) to the right then towards the basket. Brazil’s most common sequence was from the right wing to the right-top of the key and then towards the basket. Japan moved the ball from the right-top of the key to the left, then back to the right and to the elbow (top-right corner of the key). Finally, the USA’s most common sequence was moving the ball down the right side of the court to the wing and then towards the basket (Fig 6).
Effectiveness was significantly different between all teams ($F (1, 6) = 6.8, p > .001, \eta^2 = .07$) with team average effectiveness values ranging from 3.42 to 4.83. Between game effectiveness was highly variable for Australia ($F (1, 4) = 6.3, p > .001, \eta^2 = .25$) and Turkey ($F (1, 4) = 12.7, p > .001, \eta^2 = .41$), Japan ($F (1, 4) = 2.3, p = .064, \eta^2 = .01$), USA ($F (1, 4) = 2.4, p = .054, \eta^2 = .12$), Belarus ($F (1, 4) = .84, p = .5, \eta^2 = .04$), Brazil ($F (1, 4) = .91, p = .47, \eta^2 = .05$), and France ($F (1, 4) = 1.07, p = .38, \eta^2 = .05$) demonstrated much more consistent effectiveness from game to game.

Mean effectiveness values were compared in each head-to-head match-up through the tournament to test its correlation with game outcome. In 12 of 15 (80%) group games, the winning team had a higher mean effectiveness. A moderate correlation was seen between the mean standardised effectiveness differential and point differential (Pearson’s $r = 0.56$).

Finally, mean defensive effectiveness was not different between teams ($F (1, 5) = .78, p = .57, \eta^2 = .04$).
4.5 Discussion

This is the first study to quantify spatially-dependent effectiveness in basketball and provides a valuable analytical tool upon which strategies can be devised and implemented. The spatial analysis described trends in team play from the women’s 2016 Olympic basketball competition and demonstrated that overall, the right-hand side under the basket (cell 3) and the top-right 3-point area (cell 11) were the most effective areas on the court.

In general terms, the right-hand side of the court was more effective than the left, and the middle of the court was more effective than the wings. This right-side bias may be attributed to the high number of right-handed players involved in the competition, who, when dribbling on the right side of the court with their right hand, are able to keep their bodies between the defender and the ball. The centre bias is potentially the result of having more options from the centre of the court to take the ball left, right or straight towards the basket, highlighted by the effectiveness of cell 11; as well as being closer to the basket, making for higher percentage shots, highlighted by the effectiveness of cell 3. This indicates that, in general terms, defensive strategy should focus on funnelling the ball towards the left side of the court and the corners to reduce the effectiveness of the opposition. However, general defensive rules need to be tailored to suit the opponent. For example, the USA had higher effectiveness on the left side of the court and could potentially be disrupted by funnelling players to the right-hand side.

The findings of the current study are in contrast to previous research that examined the NBA 2014-15 season which showed the area under the basket had the highest value followed by the corners with the area outside the 3-point line in front of the ring (cells 10 and 11 in the current study) being of very low value (Cervone et al., 2016). While several methodological
differences exist between previous work and the current study, such as the drawing of associations between spatial utilisation and performance outcomes, the different court values provide a stimulus for future research. Potentially, significant differences exist between men’s and women’s basketball, and/or between NBA and international basketball.

The USA demonstrated the greatest overall effectiveness with above average spatial $z$-scores in all court areas with the exception of the right corner (Fig. 4). The USA were the eventual winners of the competition and the effectiveness results may provide insight into factors related to this success. The USA won by a mean differential of 37 points with the closest result coming in the semi-final against France where the USA won by 19 points. This extremely high level of success is reflected in the effectiveness results. The USA had higher mean effectiveness than any other country in 12 of the 16 cells. In four of the cells, the USA were greater than two standard deviations above the average. Spatially, the $z$-scores indicated that they were most dominant in the two cells closest to the basket (cells 2 and 3) and the mid-wing areas (cells 5 and 8). Conversely, Brazil were the only team to lose all five group games and had below average effectiveness $z$-scores for all but one cell (corner right cell 4). These examples show the two extremes of performance in the tournament, while the differences between the remaining 5 teams were more nuanced, and their performances more evenly matched, with all but Belarus progressing past the group stage. Australia were above average in the two rows of cells closest to the basket, but were below average further from the basket; Japan were particularly strong in the top of the key area; Belarus were above average on the right side of the court; Turkey had higher effectiveness on the left side of the court; and France were above average in the corners but below average through the middle of the court. The results clearly identify areas of strength and weakness for teams that are competing at an elite level. The spatial differences cannot be identified from the traditional
basketball statistics and would be very difficult to identify through observation or notational analysis because these types of analysis do not account for the ball movements throughout the entire possession.

While overall defensive effectiveness differences were not observed between teams, there were several spatial differences that existed (Fig. 5). For example, Brazil allowed the highest effectiveness in the key while Turkey allowed the lowest, suggesting that Turkey protected the key and were best at minimising the scoring effectiveness of their opponents in this region of the court. Similarly, Brazil allowed the highest effectiveness in the top of the key area followed closely by Australia, whereas Turkey once again allowed the lowest effectiveness in this area of the court. The top of the key is the most frequented area of the court and often serves as the strategic set-up point for an offence. Therefore, this region is of high strategic importance and is likely to be particularly difficult to defend because the ball carrier has the necessary space available to execute the desired offensive strategy. The lowest effectiveness for each strategic area adds further context to the analysis. For example, Turkey allowed the lowest effectiveness in the key, on the wing, and at the top of the key, whereas France allowed the lowest for the corner regions of the court. This information is valuable as it may indicate the most vulnerable area of the court for an opposing team, thereby helping to identify the area that could be exploited for a successful outcome.

The sequence analysis revealed the common sequences of ball movement through each country’s most effective cell (Fig. 6). Australia, Belarus, France, and Turkey had the same ball movement sequence which involved the ball moving from the top-middle left to the right and then towards the basket. This may suggest that these teams heavily utilised the pick-and-roll tactic in which the point guard dribbles across the top of the key to use a screen from a
team-mate before the screener cuts to the basket, usually to receive a pass from the point guard. Brazil’s most common sequence may suggest they too utilised the pick-and-roll tactic but started the move on the right side of the court instead of the more typical starting point in the left-middle area. It may also suggest a strong left-handed player who was dribbling across the court from right to left then driving to the basket. Japan moved the ball from side-to-side across the top of the key then moved it to the top-right corner of the key (also known as the right elbow), suggesting screening tactics paired with a player who was adept at executing plays around the top of the key. This is supported by the fact that Japan’s most effective areas, after cell 3, were cell 10 and 6 (top-left and left-elbow areas) suggesting they utilised the elbows on both sides of the court effectively. Japan also had the second highest effectiveness in the key, after the USA, largely because of their superior effectiveness from the elbow areas (Fig. 4). Finally, the USA sequence may suggest they had high effectiveness in cell 3 from offensive transition (otherwise known as a fast-break) down the right side of the court, alternatively the sequence could also suggest they focused on getting the ball into the right post area (the area on the edge of the key with two tick-marks). The player typically in the post is the centre and the USA’s centre was their third highest scorer and had the highest 2-point shooting percentage of all players for the tournament (70%), adding evidence to this scenario (International basketball federation [FIBA], 2016). The sequence analysis, paired with domain knowledge, has the potential to reveal important tactical and strategic information for coaches and adds important context to the spatial effectiveness results.

While this study provides novel spatial effectiveness information, the method is limited in that the length in time of the possession and the time between the ball passing through a cell and the possession ending is not considered. Future research could attempt to weight
effectiveness by time, with a spatial area having higher weighted effectiveness the closer it is to the end of the possession.

The quantification of spatial effectiveness in the current study provides insight into the specific tendencies of different teams and the areas that lead to the most effective outcomes (e.g., a score). This information can be used by coaches to devise defensive plans, as well as provide players with insight into the typical ball movement of their opponents. The sequence search provides further context by visually displaying where the opposition most commonly move the ball from different locations on the court. When combined with observational analysis, this would allow a coach or analyst to construct a comprehensive profile on an opponent and provide greater detail regarding tactics that could be employed to increase the likelihood of success. Future research should focus on extending this analysis by using court configurations other than grids, smaller cells (if the size of the data set permits) and compare across gender and/or different competitions. Finally, the sequence analysis could be extended by extracting not only a team’s most common ball movement sequence but the full range from most to least common, condition on the team’s weakest areas, or search for longer sequences if data size permits.
Chapter 4 – Study 2

4.6 References


Chapter 4 – Study 2


Appendix A. Mean standardised effectiveness values per cell for each team across all games played at the 2016 Olympic Games.

<table>
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<tr>
<th>Cell</th>
<th>AUS</th>
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<th>BRA</th>
<th>FRA</th>
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CHAPTER 5.

Study 3: The application of a Bayesian hierarchical model to basketball tracking data: testing the relationship between spatial entropy and spatial effectiveness.

5.1 Abstract

Spatial and spatio-temporal data in sport is increasing rapidly, however suitable statistical methods for analysing this data are underdeveloped. The current study establishes the need for spatial statistical methods, proposes a Bayesian hierarchical model as an appropriate method for comparing spatial variables, and test this model across three spatial scales. The need for spatial statistical methods was established through the identification of spatial autocorrelation. This necessitated the use of a Bayesian hierarchical model to test for an association between spatial ball movement entropy and spatial effectiveness. Posterior distribution results showed a generally positive association such that increases in entropy were associated with increases in effectiveness. The strength and confidence of the associations were impacted by the spatial scale, with the 6x6 grid showing the most conclusive evidence of a positive relationship; the 4x4 grid was mostly positive, however with a large variation; and finally, the basket-centric scale results were less conclusive. The results of the current study demonstrate the suitability of a Bayesian hierarchical model for testing for associations or differences between spatial variables. With the increase in spatial analyses in sport, this study presents an appropriate statistical method for dealing with complex problems associated with spatial analyses.

5.2 Introduction

Improved data collection technologies coupled with a greater appreciation of the value of analytics has led to an increase in the utilisation of data in sports. The greatest advancements have been in spatio-temporal tracking data from global and local position systems, optical tracking systems and manual tracking methods. Yet, while the volume and complexity of data in sports is growing rapidly, the development of statistical techniques to analyse this data are still needed. Spatial statistics have been applied to great effect for spatio-temporal data in
fields of research such as ecology, epidemiology and agriculture among others. Sports science and analytics research would benefit greatly from the application of these techniques to sports data sets.

Spatial data can be complex and challenging. One fundamental issue is that of spatial dependency or autocorrelation. This occurs when features of a data set are correlated as a result of being in close proximity to one another thereby violating standard statistical assumptions of independence among observations. This can increase the likelihood of making type I and type II errors and negatively affect the quality of predictions made from models (Plant, 2012). The concept of spatial autocorrelation is well established in spatial statistics however, few studies have considered its impact on sports research.

Consequently, spatial statistics commonly utilises a test for spatial autocorrelation to determine which analytical methods are most appropriate for a given dataset. The most common test is Moran’s $I$ which produces a value of $-1/(n – 1)$ under the null hypothesis of no autocorrelation. Positive values are associated with positive autocorrelation (i.e. an increase in one cell has a corresponding increase in the neighbouring cell) and negative values with negative autocorrelation (i.e. an increase in one cell corresponds to a decrease in neighbouring cell), (Cliff and Ord, 1981). Moran’s $I$ can be used with a t-test to test the null-hypothesis of no autocorrelation. Once spatial autocorrelation has been established, statistical methods that can account for spatial autocorrelation are needed.

One proposed solution to the presence of autocorrelation is the Bayesian hierarchical model. These models are ideal as their multilevel structure allows for encoded spatial dependencies in the model, reducing the possible distortion from spatial autocorrelation on the coefficients.
Furthermore, these models explicitly represent uncertainty in estimated parameters ensuring appropriate conclusions are drawn given reported confidence in modelled outcomes. The Bayesian approach also allows for high levels of complexity and correlation structures in the data, and incorporate prior knowledge of the data (Bakar and Kokic, 2017; Gelfand, 2012). These models are particularly suited to sport as they perform better than traditional methods with small sample sizes which is a key challenge for elite sports due to the limited population size (Mengersen, Drovandi, Robert, Pyne, & Gore, 2016).

Bayesian hierarchical models have been used extensively in spatial statistics whereby autocorrelation is dealt with by categorising data points into homogenous groups or regions based on their location, (Barber et al., 2017; Staubach, Schmid, Ziller, & Knorr-Held, 2002; Zhu, Gorman, & Horel, 2006). For example, if analysing student test scores across the country, a student’s test score may be grouped by school, and schools can be grouped by district and districts can be grouped by state etc. to account for differences between schools, districts and states. It also enables information sharing when estimating parameters between schools within a district, or districts within a state, which can help improve estimates when there is limited data for a particular school or district. There are many ways to define spatial regions, such as in the example, using schools or school districts, post/zip codes or grid overlays. Zhu et al. (2006) investigated the relationship between alcohol outlet densities, illicit drug use and violence in the city of Houston, Texas and grouped regions by predefined census tracts. Similarly, Biggeri et al. (2006) applied an artificial grid to the City of Naples to model risk of parasitic diseases in dogs.

Bayesian hierarchical models have been used in in a range of sports contexts including the evaluation of baseball fielders performance compared to the average player in their fielding
position (Jensen, Shirley, & Wyner, 2009), predicting the outcome of soccer matches (Baio and Blangiardo, 2010), and estimating a basketball player’s impact on their team’s chances of winning a game (Deshpande and Jensen, 2016). However, a recent literature review found no studies that explicitly modelled space in the hierarchy of a Bayesian hierarchical model (Santos-Fernandez, Mengersen, & Wu, 2019).

A second important consideration in spatial data analysis is the scale, that is, how the space is segmented. There are typically two types of spatial data; point-pattern data and areal data. Point-pattern analyses focus on the pattern of point locations, such as analysing the spatial distribution of tree locations. Areal data analysis aggregates point data into a grid and assumes data are uniform within each cell. When utilising areal data, the shape and size of cells in the grid can have a dramatic effect on the results. This is called the ‘modifiable areal unit problem’ (Plant, 2012) and there are no clear guidelines on resolving this issue.

The aim of this study is to better understand spatial effects in a sports setting by applying a Bayesian hierarchical model to a team sports dataset that appropriately tests and accounts for autocorrelation. Specifically, we aim to apply this model to spatial variables, derived from ball tracking data, measuring unpredictability and effectiveness of ball movements in basketball. The hierarchical linear model will test for associations between the two variables to find if unpredictability is associated with improved effectiveness. Three models will be used to test the relationship between the variables on three different spatial scales to find what, if any, effect the grid scale has on results.
Chapter 5 – Study 3

5.3 Methods

5.3.1 Data collection

The study was reviewed by the University of Sydney Research Integrity and Ethics Administration and deemed to be exempt from a human ethics review. Ball trajectories from 72 women’s international basketball games were manually tracked from video recordings using the bespoke software, “Pattern Plotter” (Morgan, 2007). Games were collected from a range of sources from 2014 to 2016, with 44 games from the 2016 Rio Olympic Games, 10 friendly games, 8 from the 2015 Olympic qualifying tournament, 4 from the 2015 Eurobasket competition, 4 from the 2014 FIBA World Championships and 2 from the 2015 FIBA Asia Women’s Championship Team. The six teams chosen for analysis consisted of Australia, Belarus, France, Japan, Turkey and the United States of America (U.S.A).

For each game, the ball path of all possessions was determined via manual tracking to yield x- and y-coordinate data over time. Specifically, video footage was used to estimate ball location on a virtual court with a code window allowing metadata to also be encoded (e.g., shot, turnover, foul). These data were stored in a log during the tracking process and were then exported for analysis. For more detail see Hobbs, Morgan, Gorman, Mooney, & Freeston (2018).

5.3.2 Data preparation

The 72 games of ball tracking data were pooled to test the association between spatial entropy and spatial effectiveness (defined below). Three scales were tested to show the effect of different divisions of space on the outputs. A 4x4 grid, 6x6 grid and a basket-centric configuration were tested (Fig 1). Larger grids with a greater number of cells were not
considered as the requirement for data increases with the size of the grid, therefore very large grids were not feasible. Coordinates of ball location over a possession were interpolated to return equally time-spaced coordinates by applying a smooth spline function to each possession. The x- and y-coordinates were then converted into a single location value by taking the coordinates of the ball for each second of the trajectory and transforming them into a corresponding cell. This transformation was performed over the possession, producing a vector of cell identification numbers (cell IDs) and time values for each possession.

5.3.3 Entropy calculation

To compute entropy, it was necessary to account for the varying length in time of possessions. For this the cell ID vector was segmented into five second ‘play-segments’. A sliding window was then incremented along the cell ID vector each second until it reached the end of the possession. The resulting play segments were used to fill frequency distributions over all cells. The frequency distributions contain a count of how many times the ball passed through each cell from a given starting cell across all games in the analysis. For more details on this process see Hobbs, Morgan et al. (2018). Shannon entropy was

Figure 1. Scales and regions for the 4x4, 6x6, and basket-centric scale.
calculated from the frequency distributions using the maximum likelihood estimate from the ‘entropy’ package in R (Hausser and Strimmer, 2014) given by

\[
\hat{H}^{\text{ML}} = - \sum_{k=1}^{p} \hat{\theta}_k^{\text{ML}} \log(\hat{\theta}_k^{\text{ML}}) \tag{1}
\]

where

\[
\hat{\theta}_k^{\text{ML}} = \frac{y_k}{n}
\]

and \(y_k\) is the count for each cell in the frequency distribution and \(n\) is the total number of counts.

### 5.3.4 Effectiveness calculation

A database consisting of each possession’s cell ID sequence was established. The database was searched for associations between cell IDs and outcomes of interest through association rule mining, producing results that described the frequency and likelihood of a cell being associated with an outcome. Specifically, we tested the association between the ball passing through a given cell and the outcome of the possession (positive or negative outcome) for a given team. The strength of a rule was assessed by calculating the confidence - representing the conditional probability of a positive outcome given the specified cell. Positive outcomes were defined as possessions ending in a score or shooting foul, and negative outcomes were defined as possessions ending in a missed shot or turnover. For further details see Hobbs, Gorman, Morgan, Mooney, & Freeston (2018).
5.3.5 Reliability

Reliability of the entropy and standardised effectiveness values for the current data set have been tested and presented in previous studies (Hobbs, Gorman, et al., 2018; Hobbs, Morgan, et al., 2018).

5.3.6 Bayesian hierarchical model

Associations between the two spatial measures were tested using a Bayesian hierarchical model. A hierarchical model was chosen to account for the effect of spatial autocorrelation on the results. Cells were assigned to a ‘region’ (Fig 1) that was determined to be strategically similar. A generic hierarchical model can be written as

\[
\text{Level 1: } y_i \sim p(y_i | \theta_i, \phi) \\
\text{Level 2: } \theta_i \sim p(\theta | \phi) \\
\text{Level 3: } \phi \sim p(\phi)
\]

where level 1 is the data (observed measures) which are independent according to a prior distribution that depends on the parameters \( \theta_i \); in level two the \( \theta \) parameters come from some common prior distribution that depends on the hyperparameters of \( \phi \); and level 3 says the hyperparameters \( \phi \) have some prior distributions (Gelman et al., 2013). In a normal distribution the parameters and hyperparameters referred to are the mean and variance respectively. In the case of the hierarchical regression model, the \( \theta \) parameters are the regression coefficients (intercept and slope). Therefore, the values for the intercept and slope for each region come from a prior normal distribution with some mean and variance. The dependent variable \( y_i \) is the effectiveness percentage for a given cell \( i \) between 0 and 100%. The value of \( y_i \) comes from a normal distribution with mean \( \mu_i \) and variance \( \sigma^2 \).

Level 1:

\[ y_i \sim Norm(\mu_i, \sigma^2) \]
Chapter 5 – Study 3

The mean is given by the linear regression model with intercept $\alpha$ and slope $\beta$ and the variation is given an uninformed gamma prior

Level 2:

$$\mu_i = \alpha(region[i]) + \beta(region[i]) \times x_i$$

$$\sigma^2 = \text{gamma}(0.001, 0.001)$$

The coefficients $\alpha$ and $\beta$ are matrices where the first column represents the intercepts and the second and subsequent columns represent slopes, with each row representing a spatial region.

Level 3 $\phi$ hyper-parameters comprise the priors for each parameter, as follows:

Matrix of priors

$$B[j, 1:2] \sim \text{Norm}(\hat{B}[j,], \tau [, ])$$

$$\hat{B}[j, 1] \sim \text{Norm}(0, 0.0001)$$

$$\hat{B}[j, 2] \sim \text{Norm}(0, 0.0001)$$

$$\frac{1}{\tau} = \begin{bmatrix} \sigma^2_a & \rho \\ \rho & \sigma^2_b \end{bmatrix} \text{ where } \sigma^2_a \sim \text{Unif}(0, 100),$$

$$\sigma^2_b \sim \text{Unif}(0, 100),$$

$$\tau \sim \text{Unif}(1, 1)$$

5.3.7 Selection of priors

A significant strength of Bayesian methods is the ability to apply prior knowledge to influence the posterior results. However, in order to apply priors, a strong justification is required, often based on results of previous research or meta-analyses. In this case, there are only broad indications of an association between entropy on basketball outcomes including winning games (Hobbs, Morgan, et al., 2018) and positive scoring opportunities (D’Amour, et al., 2015). There is no evidence of the effect of entropy on basketball performance
spatially. Therefore, non-informative priors (assumes no prior knowledge of data) were used in the current model.

5.3.8 Classification of spatial regions

The model accounts for spatial autocorrelation by segmenting the data into groups or ‘regions’ with homogenous spatial characteristics and resulting in the generation of regression coefficient distributions for each region, constrained by the priors. While there are numerous ways to define spatial relationships between cells, the most common way is to define a relationship as two regions which share a boundary (Plant, 2012). In sport however, these rules may not be appropriate. For example, a cell in the corner of the basketball court outside the 3-point line will be in contact with a cell closer to the basket, within the 3-point line. While they are close geographically, they have vastly different implications strategically. Therefore, using expert opinion to group cells into like regions was deemed to be more appropriate.

5.3.9 Spatial Scale

While the grouping of cells into regions can be solved with expert opinion, it is less clear how the scale will affect the results. Three scales were selected to test this – a 4x4 grid, a 6x6 grid and a basket-centric configuration (Fig 1).
5.4 Results

5.4.1 Summary of model variables

5.4.1.1 Spatial entropy

Spatial entropy was calculated as a measure of unpredictability of ball movements with higher values indicating higher unpredictability. Results show entropy values were, on average, highest in the 6x6 grid, followed by the basket-centric configuration and the 4x4 grid, meaning entropy increased with the number of cells in the scale (Fig 2). However, the lowest cell values belonged to the basket-centric grid with the two cells at the top of the key, outside the three-point line producing considerably lower entropy compared to the other cells in the court. We attribute this to the cells relatively large size, as a trend was observed for smaller cells to have higher entropy. Finally, the heat maps show a similar spatial pattern of entropy with high entropy under the basket and low entropy on the right side of the court. This pattern is not repeated in the basket-centric grid.

Figure 2. Entropy results for the 4x4 grid, 6x6 grid and the basket-centric configuration.

5.4.1.2 Effectiveness

The effectiveness values for the three scale are shown in figure 3. The highest effectiveness values for each map were under the basket, with effectiveness generally reducing with
increased distance from the basket. Of the three scales, the basket-centric configuration produced the highest overall mean effectiveness at 39.4%, while mean effectiveness was similar between the 4x4 and 6x6 scales (34.3% and 34.2% respectively), indicating how the chosen scale can affect results.

Figure 3. Effectiveness results (%) for the 4x4 grid, 6x6 grid and the basket-centric configuration.

5.4.2 Spatial Autocorrelation

Spatial autocorrelation was measured using Moran’s $I$ (Table 1). Significant autocorrelation was observed for spatial entropy and effectiveness measures within the 4x4 and 6x6 grids. Entropy was also autocorrelated within the basket-centric scale. This indicates the cell location has a significant influence on the entropy and effectiveness values and statistical techniques that account for autocorrelation are required.

Table 1. Moran’s $I$ results indicating autocorrelation within spatial variables.

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5.4.3 Bayesian Analysis

5.4.3.1 Markov Chain Monte Carlo results

The hierarchical model was fitted using Markov Chain Monte Carlo (MCMC) and convergence was checked with trace plots and Gelman and Rubin’s convergence diagnostic (refer to Appendix). Generally, a trace plot should show stationarity (mean value of the chain is reasonably stable from beginning to end) and good mixing (no identifiable pattern or correlation from one sample to the next) (McElreath, 2018). The Gelman and Rubin’s convergence diagnostic suggests MCMC chains have converged when the upper limit of the ‘potential scale reduction factor’ (PSRF) is close to 1. A large PSRF (generally > 1.2) indicates convergence failure (Gelman and Rubin, 1992).

5.4.3.2 Posterior results

The slope parameter results reveal strong evidence of a positive association between entropy and effectiveness with the area under the basket (or key area) having the most positive results (region 2 in the 4x4 grid, region 3 in the 6x6 grid and basket-centric configuration) (see regression tables in Appendix). Specifically, the 4x4 grid results showed a likelihood between 84% and 89% that the association was positive, that is, increased entropy was associated with increased effectiveness \((x = 0.26 + -0.31)\). The 6x6 grid showed a likelihood between 96% and 100% that the association was positive \((x = 0.39 + -0.14)\). The basket-centric grid showed a likelihood between 58% and 67% that the association was positive, \((x = 0.03 + -0.13)\). Finally, the model produced values for the y-intercept coefficient (Fig 5).

While the majority of these values were negative, effectiveness cannot have a negative value. Therefore, understanding what the value of effectiveness would be when entropy is 0, as the y-intercept indicates, is not meaningful to the current study.
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Figure. 4. Slope value distributions with median line for the 4x4, 6x6 and basket-centric (BC) scales with a separate distribution for each region within the scale.
Figure. 5. Intercept value distributions with median line for the 4x4, 6x6 and basket-centric (BC) scales with a separate distribution for each region within the scale.

5.5 Discussion

The current study showed that common issues related to spatial datasets exist in sport, specifically spatial autocorrelation and the modifiable areal unit problem. These problems require appropriate statistical treatment which have been lacking in the scientific literature relating to spatial or spatio-temporal analyses in sport. The current study found statistically significant autocorrelation in five of six analysed spatial variables (entropy and effectiveness across three spatial scales). Therefore, a Bayesian hierarchical model was used to test for associations between the two spatial variables that accounted for these correlation structures.
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The results showed a general positive association between spatial entropy and spatial effectiveness with generally high confidence across the three spatial scales tested. These findings effectively demonstrate the utility of the model in comparing spatial variables in sport.

While each of the three scales demonstrated associations between the two variables, the conclusions drawn from each scale varied, indicated by the proportion of the distribution that was positive (Fig 4). The 6x6 grid results suggest an almost certain positive relationship such that every 0.1 increase in entropy was associated with an increased effectiveness of between 3.6% (region 8) and 4.7% (region 3) based on mean slope values. Similarly, the 4x4 grid results showed an entropy increase of 0.1 was associated with an increased effectiveness of between 2.4% (region 4) and 3.2% (region 2). While the mean values for the two grids were comparable, the meaningful difference was seen in the mean standard deviation (0.31 vs 0.14). This suggests the model is significantly less certain about the association of the two variables for the 4x4 grid. Finally, the basket-centric results showed an increase of effectiveness between 0.2% (region 4) and 0.6% (region 3) suggesting a likely positive, though minimal, relationship. These results correspond with previous research that found a positive impact of entropy and performance in basketball and football. Hobbs, Morgan et al. (2018) showed that winning teams in international women’s basketball played with significantly higher entropy than losing teams; a similar relationship was shown in soccer with higher entropy of ball passes between players from English Premier League football correlated with the team’s position at the end of the season (Neuman, Israeli, Vilenchik, & Cohen, 2018).
The results from the three scales demonstrate the effect of spatial partitioning on the variables, which in turn, affect the outcome of statistical tests and the conclusions that can be drawn from them. If each grid was considered separately, three different conclusions could be drawn. The 6x6 grid showed conclusive evidence of a positive relationship between entropy and effectiveness with differing degrees between regions. The basket-centric results contained less variation but also less conclusive evidence of the association. Finally, the 4x4 grid revealed large variation within each region, represented by the wide distributions of parameters (Fig 4 and 5). There is no clear consensus in the literature regarding the appropriate selection of scale and is ultimately up to the user to decide based on domain knowledge and understanding of the variables being tested. From the results of the current study combined with domain knowledge, the basket-centric scale is recommended for further study. This model produced the lowest variation in parameter distribution densities, and the spatial structure clearly segments strategically important areas of the basketball court, such as using the 3-point line as a divider and segmenting the corner 3-point area and the key area. Importantly, the decision should not be made by choosing the scale that gives the most positive results or most agrees with the hypothesis.

The current study demonstrates the applicability of Bayesian hierarchical models for testing associations between spatially autocorrelated variables. These models are highly versatile and can be extended to make predictions on unseen data as well as be used with spatio-temporal data. Furthermore, if strategically important regions are less clearly defined, such as in sports with large playing areas like soccer or Australian Rules football, a more common grid structure can be used with regions defined by location. These models define regions based on cell neighbourhoods and may better represent the spatial relationships for appropriate sports. Future research producing spatial or spatio-temporal variables should strongly consider the
use of Bayesian hierarchical models as a robust and flexible method for modelling these variables.
5.6 References


Morgan, S. Pattern Plotter (Version 4.5x) [Computer Software]. Australian Institute of Sport.


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5.7 Appendix

Figure A1. Trace plot for 4 x 4 grid.

Figure A2. Trace plot for 6 x 6 grid
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Figure A3. Trace plot for basket-centric configuration.

Table A1. Regression table and Gelman and Rubin’s convergence diagnostic (PSRF) for the 4x4 grid.

<table>
<thead>
<tr>
<th>4x4</th>
<th>Coefficient</th>
<th>Mean</th>
<th>Upper Credible Interval</th>
<th>Lower Credible Interval</th>
<th>PSRF</th>
<th>PSRF (upper limit)</th>
</tr>
</thead>
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<td>-0.24</td>
<td>1.18</td>
<td>-1.75</td>
<td>1.01</td>
<td>1.02</td>
<td></td>
</tr>
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</tr>
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<td>1.02</td>
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</tr>
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</tr>
<tr>
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Table A2. Regression table and Gelman and Rubin’s convergence diagnostic (PSRF) for the 6x6 grid.

<table>
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<tr>
<th>6x6</th>
<th>Mean</th>
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</tr>
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Table A3. Regression table and Gelman and Rubin’s convergence diagnostic (PSRF) for the 6x6 grid.

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</table>
### Chapter 5 – Study 3

<table>
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CHAPTER 6.

Study 4: Does increased entropy of ball movements prior to a shot improve likelihood of scoring in international women?
6.1 Abstract

Recent research has demonstrated a link between unpredictability and performance in team sports. However, few studies have measured this relationship using appropriate metrics or statistical methods. The aim of this study was to measure terminal entropy (unpredictability of ball movements in the final five seconds of possessions) and scoring efficiency across the court and test their relationship using Bayesian hierarchical models. The results showed entropy of ball movement in the five seconds preceding a shot was positively associated with scoring efficiency. The association is strongest when a shot is taken from within the key. Results were not consistent across the six countries in the study with Australia showing the greatest association between entropy and scoring efficiency, followed by Japan, the USA and France, while Belarus and Turkey showed a weaker relationship. These findings have significant implications for the development of offensive and defensive strategies in basketball, such that strategies designed to increase ball movement entropy prior to a shot may improve the likelihood of shot success, especially for shots close to the basket.

6.2 Introduction

Scoring in basketball occurs at a high frequency, on average 40 times per game per team in women’s international basketball (including those ending in free throws). Therefore, the defensive team has many opportunities to learn the opposing team’s offensive tendencies during the game. In addition, it is common practice to analyse the opposition prior to games to uncover tendencies of the opposing team. Therefore, coaches and players have ample information to design and implement defensive strategies. In response, offensive strategies and tactics are designed to deceive or disrupt defences, increasing the likelihood of scoring. Skinner (2010) described basketball offensive strategy from a game theory perspective, arguing that the team’s highest percentage play (pre-designed possession) would become less
effective each time it is used. This is because the defence would adapt and learn. Therefore, it has been argued that unpredictability on offence is an important component of modern offences and leads to better scoring opportunities (D’Amour, et al., 2015).

The effect of unpredictability on performance in team sports has received increased attention in recent years. Lucey et al. (2012) used ball tracking information to measure entropy (a way of quantifying unpredictability in time series data) of soccer team offences throughout a season of the English Premier League. The study was methodologically focused and did not link results to performance outside season rankings. Hobbs, Morgan et al. (2018) calculated spatial entropy for six international women’s teams based off tracked ball movements. The study showed winning teams played with significantly higher entropy than losing teams. These studies made links to the effect of entropy on performance, using final competition ranking or winning/losing a series of games as outcomes. These broad definitions of performance imply some relationship, however more precise measures are needed to further investigate this association.

One study was found using player and ball tracking data (all players and the ball are tracked throughout the game) which established a correlation between ball movement entropy and the probability of future open shots (D’Amour, et al., 2015). This study provides further evidence for unpredictability as a successful strategy in basketball with more robust performance measures. However, player tracking data is not widely available and restricted access to the data means the findings are difficult to replicate or advance. Therefore, there is a need for more cost effective and less labour-intensive approaches that can provide contextual information to a broader range of sports and levels of competitions.
Chapter 6 – Study 4

The extent to which teams apply the strategy of unpredictability makes up only one element of their overall team style of play. Teams must strike a balance between unpredictability and team organisation and cooperation. Consequently, the results will shed light on how different teams approach the problem of playing unpredictability while attempting to score efficiently, providing further understanding of team style of play in basketball. Therefore, the current study aims to test if ball movement entropy in the five seconds preceding a shot (here on referred to as terminal entropy) affects shooting efficiency across the court. Rather than focusing on broad measures of performance such as season rankings or win/loss record, we will model the effect of terminal entropy and the resulting shooting performance.

6.3 Methods

6.3.1 Data collection

The study was reviewed by the University of Sydney Research Integrity and Ethics Administration and deemed to be exempt from a human ethics review. Ball trajectories from 60 women’s international basketball games (6 teams and 10 games each) were manually tracked from video recordings using the bespoke software, “Pattern Plotter” (Morgan, 2007). The games included took place between 2015 and 2016 from the 2016 Rio Olympic Games, Olympic Qualifying competition (2016), 2015 Eurobasket competition and the FIBA Asia women’s championship. The teams included in the study were Australia, Belarus, France, Japan, Turkey and the United States of America (USA). Team selection was a strategic decision aligned with the interests of the Australian Women’s Basketball team’s coaching staff for the 2016 Olympic Games as Australia were to play each team in Group A, while the USA were (and remain) the current world and Olympic champions.
For each game, the ball path of all possessions was determined via manual tracking to yield x- and y-coordinate data over time. Publicly available video footage was used to estimate ball location on a virtual court with a code window allowing metadata to also be encoded (e.g., shot, turnover, foul) within the Pattern Plotter software. These data were stored in a log during the tracking process and were then exported for analysis (Hobbs, Morgan, et al., 2018).

6.3.2 Data preparation

The front-court was divided into a 20-cell irregular grid and grouped into five regions for further analysis (Fig 1). Regions were defined by grouping strategically similar cells. Coordinates of ball location were interpolated to return equally time-spaced coordinates by applying a smooth spline function to each possession. This was performed because the entropy calculation requires an equally spaced time series, while the data collection method records the ball location on each click of a mouse, and therefore were not equally spaced. The interpolated x- and y-coordinates were then converted into a single location value by taking the coordinates of the ball for each second of the trajectory and transforming them into the corresponding cell. This transformation was performed over the possession, starting from when the ball crossed the halfway line, producing a vector of cell identification numbers (cell IDs) and time values for each possession. For further details on this process see (Hobbs, Morgan, et al., 2018).
6.3.3 Terminal entropy calculation

Entropy was calculated by first computing the cell IDs for the last 5 seconds of each possession ending in a shot or shooting foul. Each cell was assigned a matrix and when a shot was taken in a given cell, the cell IDs that lead to the shot were recorded for that cell in the matrix. Thereby, through 10 games of data, each cell has a frequency distribution showing counts of cells that led to a shot from that cell location. Shannon’s entropy was calculated from the frequency distributions using the maximum likelihood estimate from the ‘entropy’ package in R (Hausser and Strimmer, 2014). Reliability for entropy measures using the current dataset was established and presented (Hobbs, Morgan, et al., 2018).

6.3.4 Shooting efficiency calculation

Efficiency in the current study is analogous to a standard shot chart, showing the number of shots made divided by the number of total shots for each cell. The only addition being that shooting fouls were included and regarded as a successful shot. This is to represent the positive impact of a shooting foul in basketball, not only leading to two free throws (with a
76% shooting percentage in the tournament), but also adding a foul to the limited number of fouls allowed for players and teams before a penalty is given. To account for the varying number of possessions used to calculate efficiency for each cell, a standardisation calculation was used. This was necessary as a cell x may have 40 shots, of which 40% were successful, while cell y may only have 16 shots of which 50% were successful - leaving the question of which cell was more productive. By dividing the proportion by the approximate standard deviation of the proportion, we get a standardised value of 5.2 for cell x and 3.9 for cell y, scaling down the over-confident 50% value for cell y. Specifically, the proportion was divided by the approximated standard deviation of the proportion using the equation (1) below where SE = standardised effectiveness, p = proportion and n = the count of possessions:

\[
SE = \frac{p}{\sqrt{\frac{p(1-p)}{n}}}
\]  

(1)

Figure 2 shows the mean shooting efficiency % (pre standardisation), counts of shots and shooting fouls, and resulting standardised shooting efficiency across all teams. Finally, shooting percentage is often adjusted to account for the higher value of 3-point shots using ‘effective field goal percentage’, defined as

\[
eFG\% = \frac{FGM + (0.5 \times 3PTM)}{FGA}
\]  

(2)

where FGM is field goals made, 3PTM is 3-point field goals made and FGA is total field goal attempts. While this is a useful adjustment in most cases, in the current study there were instances where a high percentage of 3-point shots were made from a cell leading to an
effective shooting % above 1. A percentage cannot be over 1, therefore, it was decided not to implement this adjustment.

Figure 2. A. The mean shooting efficiency % across all teams for each cell. B. The mean count of shots and shooting fouls. C. The standardised shooting efficiency calculated from the shooting efficiency % and count of shots and shooting fouls.

6.3.5 Data analysis

6.3.5.1 Bayesian hierarchical model

Terminal entropy and scoring efficiency were tested for association using a Bayesian hierarchical model. These models have been shown to be ideal for spatial comparisons in sporting contexts as they are well equipped to handle small amounts of data (in the current study, 4 cells for each of the 5 regions) and provide distributions of likely values for model parameters that indicate their uncertainty (Santos-Fernández, Wu, & L Mengersen, 2019).

Cells were assigned to a ‘region’ (Fig 1) that was determined to be strategically similar. This step accounts for differences arising from spatial contexts, such as cells under the basket naturally having higher efficiency than cells further from the basket. The aim of the model was to quantify the association between the two spatial variables while accounting for ecological differences between regions. A generic hierarchical model can be written as
where level 1 is the data which are independent according to a prior distribution that depends on the parameters $\theta_i$; in level two the $\theta$ parameters come from some common prior distribution that depends on the hyperparameters of $\phi$; and level 3 says the hyperparameters $\phi$ have some prior distributions. For a normal distribution the parameters are the mean and variance. In the case of a hierarchical regression model, the $\theta$ parameters are the regression coefficients (intercept and slope). Therefore, the values for the intercept and slope for each region come from a prior normal distribution with some mean and variance. The value of $y_i$ comes from a normal distribution with mean $\mu_i$ and variance $\sigma^2$.

Level 1 – the likelihood:

$$y_i \sim \text{Norm}(\mu_i, \sigma^2)$$

The mean of the likelihood distribution is given by the linear regression model with intercept $\alpha$ and slope $\beta$ with Gaussian priors. The variation is given by a prior Cauchy distribution

Level 2:

$$\mu_i = \alpha(\text{region}[i]) + \beta(\text{region}[i]) \times x_i$$

Standard deviation within regions prior: $\sigma^2 = \text{cauchy}(0, 2)$

Mean intercept prior: $\alpha = \text{Normal}(0, 10)$

Mean slope prior: $\beta = \text{Normal}(0, 10)$

Level three defines the population of varying intercepts and slopes. The following line of the model states that each region has an intercept $\alpha$ and slope $\beta$ with a prior distribution defined by a two-dimensional Gaussian distribution with means $\alpha$ and $\beta$ and covariance matrix $S$. 
This prior will adaptively regularise the individual intercepts, slopes and the correlation among them.

Level 3:

\[
\begin{bmatrix}
\alpha_{\text{Region}} \\
\beta_{\text{Region}}
\end{bmatrix}
\sim MVNormal\left(\left[\begin{array}{c}
\alpha \\
\beta
\end{array}\right], S\right)
\]

The matrix $S$ is the covariance matrix containing separate standard deviations, $\sigma_\alpha$ and $\sigma_\beta$, and a correlation matrix $R$.

\[
S = \begin{pmatrix}
\sigma_\alpha & 0 \\
0 & \sigma_\beta
\end{pmatrix}
R
\begin{pmatrix}
\sigma_\alpha & 0 \\
0 & \sigma_\beta
\end{pmatrix}
\]

Standard deviation among intercepts prior: $\sigma_\alpha = \text{cauchy}(0, 2)$

Standard deviation among slopes prior: $\sigma_\beta = \text{cauchy}(0, 2)$

Correlation matrix prior: $R = \text{LKJcorr}(1)$

The primary results from the model are the intercept and slope parameters for each region and team. These parameters together will describe the magnitude (positive or negative) of the association between terminal entropy and efficiency. A positive slope indicates an increase in entropy is associated with an increase in efficiency. The Bayesian model will produce distributions for intercept and slope parameters with means and standard deviations. The intercept parameters are of less interest, as a terminal entropy result of 0 is not possible, the corresponding value of efficiency when entropy equals 0 is not useful.

### 6.3.5.2 Selection of priors

Previous research indicates a positive association between entropy and performance (Hobbs, Morgan, et al., 2018; Hobbs, et al., 2019 under review; D’Amour, et al., 2015). However, terminal entropy and shooting efficiency have not been compared previously. Therefore, only
slightly informed priors were used for the mean intercept and slope that assumed a flat relationship with a standard deviation of 10. Half-Cauchy distribution priors (a Cauchy defined over the positive real numbers only) were used for all standard deviation parameters. The Cauchy distribution is a thick-tailed distribution that provides a weak regularisation for the standard deviation. Finally the LKJcorr distribution defines a weakly informative prior on the correlation in the covariance matrix, meaning it is sceptical of extreme correlations near -1 or 1 (McElreath, 2018).

6.4 Results
6.4.1 Terminal Entropy
Terminal entropy was calculated for each team (Fig 3). The three major regions (key, mid-range and three-point area) showed consistency across the majority of countries with highest mean values in the key, followed by 3-point regions and lowest mean entropy for the mid-range regions. This order was consistent for all countries apart from Turkey, in which entropy was higher for mid-range cells than three-point cells. Overall mean terminal entropy values were, from highest to lowest, Japan (2.56 ± .16), Australia (2.55 ± .18), Turkey (2.52 ± .19), France (2.47 ± .21), USA (2.45 ± .26), and Belarus (2.43 ± .28). By region (defined in Fig 1), region 3 had the highest mean entropy with 2.73 ± .05, followed by region 5 with 2.54 ± .04, region 2 with 2.46 ± .15, region 1 with 2.45 ± .08, and region 4 with 2.3 ± .1. Therefore, entropy of ball movements were highest prior to a shot from the key, and lowest for shots taken from the middle 2-point range.
6.4.2 Scoring efficiency

Standardised scoring efficiency for each team can be seen in Fig 4. The results show cells 3 and 4 (closest to the basket) consistently have the highest efficiency. These cells are considerably higher because they had both the highest usage of any cell (meaning the most shots or shooting fouls recorded) and the highest shooting percentage. By country, the USA had the highest mean scoring efficacy of $6.34 \pm 4.77$, followed by Belarus with $5.06 \pm 3.15$, Japan with $4.79 \pm 3.27$, France with $4.45 \pm 2.54$, Turkey with $4.32 \pm 2.73$ and Australia with the lowest of $4.26 \pm 3.4$. Mean efficiency by region showed region 3 had the highest mean efficiency of $9.86 \pm 4.49$, followed by region 2 with $3.83 \pm .59$, region 1 with $3.73 \pm .61$, region 5 with $3.58 \pm .34$, and region 4 with the lowest mean of $3.36 \pm .6$. 

Figure 3. Terminal entropy heatmaps for each team
6.4.3 Associations between entropy and efficiency

The hierarchical model was fitted using Markov Chain Monte Carlo (MCMC) and convergence was checked with trace plots (Appendix Figs 1-6). The Bayesian model results indicate that increased entropy was associated with increased shooting efficiency. Every team showed an association between entropy and effectiveness such that higher entropy led to greater shot success. However, the strength of this association varied across countries, suggesting some countries may benefit more from higher entropy. All teams showed the most positive regional association for region 3 (the key area) (Fig 5). While the raw data indicates strongly positive relationships for this region across all teams, the model constrained these extremely positive slope values, decreasing them closer to the global slope parameter mean to avoid overfitting the data. To quantify the likelihood of a positive association, the proportion of plausible slope values greater than 0 were calculated. Results showed Australia and Japan
had a 97% likelihood of a positive association, France and the USA had 95% and 94% likelihoods respectively, Turkey a 75% likelihood, Belarus a 67% likelihood.

Figure 5. Posterior slope distributions for each team and each region with box plot. Each dot is a simulated draw from a distribution of likely slope values based on the raw data.

The practical implications of the mean slope values typically state that an increase in $x$ (entropy) of 1 is associated with a corresponding increase in $y$ (efficiency). This is an unhelpful interpretation, as the whole range of entropy values across all countries is just over 1, from a low of 1.85 to a high of 2.86 in the current study. Therefore, using an increased entropy of 0.5 as a benchmark may be more appropriate. Using this standard, Australia had
the strongest relationship across all regions, with a mean increased efficiency of 4 when entropy increased by 0.5. Conversely, Belarus had the weakest relationship with a mean increased efficiency of 0.6 (Table 1). Furthermore, there were differences in the variance of posterior distributions with Australia, Japan and the USA having a standard deviation of 4.2, 3.8, and 4.1 respectively, while Belarus, France and Turkey were 3.1, 2.9, and 2.7. This indicates the model’s confidence in the results, with wider distributions suggesting less certainty around the mean.

Table 1. Mean increase in efficiency for each 0.5 increase in entropy for each country and region.

<table>
<thead>
<tr>
<th>Country</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>3.9</td>
<td>3.9</td>
<td>4.3</td>
<td>4.0</td>
<td>3.9</td>
<td>4.0</td>
</tr>
<tr>
<td>Belarus</td>
<td>0.5</td>
<td>0.5</td>
<td>1.1</td>
<td>0.5</td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td>France</td>
<td>2.4</td>
<td>2.3</td>
<td>2.7</td>
<td>2.4</td>
<td>2.3</td>
<td>2.4</td>
</tr>
<tr>
<td>Japan</td>
<td>3.4</td>
<td>3.5</td>
<td>3.9</td>
<td>3.5</td>
<td>3.4</td>
<td>3.5</td>
</tr>
<tr>
<td>Turkey</td>
<td>0.8</td>
<td>0.9</td>
<td>1.3</td>
<td>0.7</td>
<td>0.8</td>
<td>0.9</td>
</tr>
<tr>
<td>USA</td>
<td>3.1</td>
<td>3.1</td>
<td>3.7</td>
<td>3.1</td>
<td>3.0</td>
<td>3.2</td>
</tr>
</tbody>
</table>

6.5 Discussion

This is the first study to demonstrate an association between entropy of ball movements and scoring efficiency in basketball. Specifically, the variability in ball movement in the five seconds preceding a shot is positively associated with scoring efficiency. This association is strongest when a shot is taken from within the key. These findings have significant implications for the development of offensive and defensive strategies in basketball, such that strategising to increase ball movement entropy prior to a shot may improve the likelihood of shot success, especially for shots close to the basket.
Australia showed the strongest positive relationship across the five regions, followed by Japan, the USA and France, while Belarus and Turkey’s results showed less conclusive evidence of a relationship. Furthermore, there were observed differences in the model’s confidence of parameter values, indicated by posterior distribution’s standard deviation with Australia, Japan and the USA showing higher uncertainty compared to Belarus, France and Turkey. This suggests that, based on the raw data and the prior distributions, there were a wider range of plausible slope values for those countries with wider distributions.

Importantly, a stronger association does not always result in better performance. Australia had the strongest association and Belarus had the weakest, however as shown in Fig 4 Belarus generally had better shooting efficiency. This suggests Australia require higher terminal entropy to generate better scoring opportunities, while Belarus are less reliant on it and use other strategies to generate scoring opportunities.

The findings from the current study align with previous investigations of the impact of entropy on performance in team sports. As previously mentioned, (Hobbs, Morgan, et al., 2018) showed entropy of ball movements throughout the entire basketball possession was significantly higher for winning teams compared to losing teams. The study also found entropy was highest for teams that won by 10 points or more. Similarly, Hobbs et al. (2019) found a positive association between entropy and scoring effectiveness (a measure of the likelihood of scoring from various positions across the court throughout a possession) across a sample of 72 international women’s basketball games. Finally, Neuman et al. (2018) found passing entropy in English Premier League football was positively correlated with end of season ranking. This amounts to compelling evidence of the role entropy plays in performance in team sports.
While there is mounting evidence that unpredictability, measured as entropy in different forms, is strongly associated with improved performance, it is only one element of a team’s overall game or tournament strategy. Therefore, results found in the current study should not be interpreted as a causal relationship. Many complex factors make up overall performance, and while effectively maximising entropy of ball movements may optimize team performance, it does not mean that team will win. However, evidence does suggest it may increase the likelihood of winning, by improving shooting efficiency, which has been shown to be one of the most important factors in winning basketball games (Oliver, 2004).

The current study provides insights into team style of play, as shown by the magnitude of the relationship between terminal entropy and shooting efficiency. This relationship is a feature of a team’s strategy, whereby a team may try to be more unpredictable, or move the ball with greater variability prior to a shot. While this may not be a conscious effort during a single possession, it is likely a component of team strategy designed by the coaching staff. Beyond being able to quantify this relationship, the current method can be used as a way of quantifying the effectiveness of terminal entropy for coaches trying to optimise unpredictability in their strategy. Furthermore, opposition coaches can use this information to design defensive strategies. For example, if there is a strong association between terminal entropy and shooting efficiency, a greater focus may be directed towards limiting ball movement through various defensive strategies. Conversely, if a team does not have a clear association such as Belarus, it may suggest the team does not rely on ball movement entropy to score. Therefore, the focus may shift to the team’s shooting efficiency maps to see where they are most efficient and consider other strategic features used to score. Future research should focus on understanding why ball movement entropy is positively associated with shooting efficiency, explore differences in playing style between those teams with a strong
positive association and those with weaker associations, and finally examine different cohorts to test if these relationships are typical across basketball or specific to women’s international basketball.
Chapter 6 – Study 4

6.6 References


Chapter 6 – Study 4

6.7 Appendix

Figure A1. Australia trace plots.

Figure A2. Belarus trace plots.
Chapter 6 – Study 4

Figure A3. France trace plots.

Figure A4. Japan trace plots.

Figure A5. Turkey trace plots.

Figure A6. USA trace plots.
CHAPTER 7.

Thesis Discussion

In a co-sponsored partnership with Basketball Australia and the Australian Institute of Sport, this project set out to investigate collective behaviour and its relationship to performance in international women’s basketball. We aimed to (i) better understand opponents, (ii) better understand own game-play as well as (iii) understand what leads to success more generally. A literature review was conducted (Chapter 2) to examine how collective behaviour had been investigated previously across all team sports and how this information had impacted performance. The review found a total of 84 relevant articles spanning 36 years and showed a significant increase in the number of studies involving spatio-temporal data from approximately 2012 onwards. This data facilitated a range of new research themes from dynamic systems, spatial analyses, network analysis, and machine learning based strategy analysis. The quality of research varied widely however, with the majority of studies limited by a small sample size (one to three games) and/or a failure to adequately define the reliability of data collection methods. Reporting reliability was particularly pronounced for
spatiotemporal tracking research, with no articles in the review stating reliability of data collection methods. This review highlighted a need for higher quality research generally, including appropriately sized data sets and adequate reporting of data collection reliability. Furthermore, it became evident that a significant shift was occurring in the scientific literature towards the application of spatiotemporal data towards collective behaviour problems. Problematically however, this data is not always readily available, with collection systems prohibitively expensive, or restricted due to competition rules such as in non-professional settings like the Olympic Games competitions. Therefore, the identified gap in research literature necessitated the development of a valid and reliable, yet cost-effective solution for the analysis of collective behaviour using spatio-temporal data.

In partnership with Basketball Australia this project aimed to study collective behaviour and its impact on performance among international women’s basketball in the hope of advancing our understanding of factors leading to successful performance within Olympic competition. The context of this project therefore required a coach-centred approach. Consequently, the literature review was necessarily broad, describing collective behaviour research across all team sports, identifying trends and possible future research. The coaching staff of the Australian women’s basketball team had a specific interest in understanding the impact of differing degrees of structure within the team’s playing style. Less structure within the offensive scheme was assumed to be related to unpredictability of play. Consequently, unpredictability was identified as a central theme that could be further explored so as to both align with coach-centred problems while simultaneously investigating an under-researched area of collective behaviour research.
Chapter 7 – Discussion

The purpose of chapter three was to develop and apply a method to describe the level of unpredictability in basketball offences. Utilising custom, cost-effective ball tracking software, a valid and reliable method was adapted from Lucey et al. (2012) that quantified the spatial variability in ball movement for five second segments of basketball possessions. The basketball court was divided into cells and a frequency distribution was generated as the ball passed through each region of the court. These frequency distributions allowed unpredictability to be described in the form of Shannon’s entropy. This analysis revealed that teams that won by 10 points or more played with significantly higher entropy than those that lost by 10 points or more. When the front-court was considered in isolation, teams that won demonstrated significantly greater entropy than losing teams regardless of the margin. Interestingly however, no significant differences were found between teams which suggested that the measure was not sensitive enough, the statistical tests were not sensitive enough, and/or there was no discernible difference in entropy between teams in the study.

The association between entropy and a broad measure of success (margin-defined wins or losses) identified in chapter 3 provided stimulus for further research. To further explore the relationship between unpredictability and performance required a more precise measure of performance. Chapter four developed and applied a novel performance metric termed spatial effectiveness that quantified offensive performance on the same spatial scale as entropy. This allowed for a direct comparison of the two variables to test for a relationship. At the time of study commencement (2016) only two publications were found in the scientific literature that measured entropy of team sport gameplay and had linked it to performance (D’Amour, et al., 2015; Lucey, et al., 2012). D’Armour (2015) tested performance with bespoke measures related to scoring opportunity using data that was not unavailable for the current study nor is commonly available for many applications outside of the NBA etc, and the latter used season
Chapter 7 – Discussion

ranking, a very broad measure of effectiveness that lacks sensitivity. The purpose of chapter 4 was to develop a valid method to quantify the likelihood of scoring when the ball passed through different regions of the court, thereby, highlighting the areas of scoring strengths and weaknesses of different teams (using spatial effectiveness z-scores). In addition, the newly developed method was capable not only of identifying each team’s most commonly occurring ball movement sequences but could also identify the most commonly occurring sequence for any given cell. An important feature of this method was that the effectiveness metric was capable of measuring performance on the same scale as entropy. Therefore, a direct correlation could be performed to test the effect of entropy on performance across the court.

With entropy and effectiveness metrics investigated and established, an appropriate statistical procedure was needed to test the association between the two metrics. Chapter 5 introduced the Bayesian hierarchical model to model the linear relationship between entropy and effectiveness while accounting for identified spatial autocorrelation in the data. While this method had been used to compare spatial variables in other research fields such as ecology and sociology, it had not been used in sport. Importantly, the concept of spatial autocorrelation had not yet been considered in sports performance analysis research, nor was there a defined method for modelling spatial variables. The Bayesian model was constructed using entropy and effectiveness values from 72 international women’s basketball games to test if there was an association between the two variables, while controlling for spatial autocorrelation by grouping the 20 cells into 5 groups of 4 cells each. The model provided a robust framework to test this association, resulting in distributions of likely model parameters that reflect the uncertainty of results. Furthermore, the study demonstrated that results can differ depending on how the court is divided. We tested a 6x6 grid, a 4x4 grid and a basketball-centric scale. Autocorrelation was found in all three spatial scales, justifying the
use of Bayesian model. The results from the 6 x 6 grid indicated an almost certain positive relationship between entropy and effectiveness, with a more positive slope for cells close to the basket. This indicates that higher entropy was associated with greater effectiveness, especially in regions closer to the basket. Similarly, the 4 x 4 grid results showed a largely positive relationship, while the basket-centric map results suggested less certainty of a relationship between the two metrics. This study provided a robust statistical method for comparing spatially autocorrelated variables and provided strong evidence for a positive effect of ball movement entropy on spatial effectiveness in international women’s basketball.

Study four was designed to more directly examine this relationship while adapting the methods established previously in the thesis. In the previous studies, entropy and effectiveness were measured over the entire possession. However, with a vast range of other factors that could impact entropy and effectiveness throughout a possession, more precise metrics were established to examine the specific ball movement patterns that occurred prior to a shot being taken. Entropy was calculated by recording the cells the ball passed through in the 5 seconds prior to a shot being taken or a shooting foul occurring, termed terminal entropy. To measure performance, shooting efficiency was calculated for each cell, describing the percentage of successful shots or shooting foul out of the total number of shots. Using a Bayesian hierarchical model as in chapter 5, slope and intercept distributions were produced for each team to compare their spatial association with terminal entropy and scoring efficiency. The results overwhelmingly showed that shooting efficiency increased with higher entropy of ball movements prior to a shot. Significant differences between countries existed however, with Australia, France, Japan and the USA showing a strong positive relationship between entropy and effectiveness in each region across the court, while Belarus and Turkey’s results suggested a likely positive relationship but with less certainty.
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This may indicate that Belarus and Turkey played a similar style of basketball, or that they are less reliant on unpredictability prior to a shot for generating scoring opportunities. While, Australia, Japan and the USA appeared to require high ball movement entropy prior to a shot in order to generate high scoring efficiency.

The findings of this thesis suggest that better performance in basketball is associated with increased unpredictability of ball movement, both during the entire possession and in the final five seconds of a possession. This is an important finding that is supported by previous research. It has been shown that open 3-point shots have a higher shooting percentage (Lucey, Bialkowski, Carr, et al. 2014). The study further showed that more dribbling led to more pressured shots and more passing led to more open shots, suggesting ball movement prior to a shot is important. Furthermore, the less distance the defence (as a whole) had to travel in the three seconds prior to a shot the more likely they were to put pressure on the shooter. This was shown to be related to defensive role-swapping, in which the defenders have to move out of their defensive formation, creating instability in the defensive structure. D’Amour, et al. (2015) also showed the importance of ball movement, suggesting it introduced unpredictability into offenses, creating greater opportunities to score. The thesis findings extend this discussion, showing entropy of ball movement led to more wins, greater spatial scoring effectiveness and greater shooting performance in women’s international basketball.

7.1 Implications

The body of work comprising this thesis presents a range of implications relevant to coaches, performance analysts and researchers. Most notably, we have provided strong evidence confirming the presence of an association between higher entropy and performance in
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basketball, be it winning games, spatial effectiveness or shooting efficiency. Consequently, basketball strategy should incorporate greater variability in ball movements, particularly in the small window prior to a shot in order to maximise shooting efficiency.

7.1.1 Implications for Basketball Coaching and Analytics

The current thesis developed a novel method for testing the relationship between unpredictable behaviour and effectiveness that can be applied to other basketball contexts as well as other team sports. Specifically, we developed methods to describe unpredictability, methods to define effectiveness, as well as statistical methods to assess their relationship while accounting for spatial autocorrelation which, while common in other disciplines, has not to our knowledge been applied to the field of sport science research. Significant advantages of the current method are that the data can be collected in real time with relatively simple software, with a small collection of games (5 or more), and can be used to evaluate if players are executing the desired game plan of high ball movement variability. Similarly, coaches and analysts can use the technique to better understand opponents, by identifying areas of low entropy and investigating exactly what teams do from those areas on the court. This may be achieved by using the ball movement sequence analysis presented in chapter 4, allowing a coach or analyst to specify the team and court location and search the data for the most commonly occurring ball movement patterns. Alternatively, it may simply highlight areas of the court the coach may want to focus on when scouting opposition teams.

Chapter 4 provided a way for coaches, analysts and researchers to quantify the effectiveness of their ball movements across the court. This can be used to evaluate the success of tactical and strategic goals, identify areas of strengths and weaknesses, and scout opposition teams. Alternatively, it can be used, as it was in chapter 4, as a performance measure to test against
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other spatial variables. The sequence analysis is a complimentary tool that can be used to find the most commonly occurring, and least commonly occurring ball movement sequences from any cell on the court.

Chapter 5 details the methodology needed to compare spatial variables. With the rise of spatial analyses in sport, both in research and practice, the Bayesian hierarchical model can be used to test for associations between spatial variables by grouping the playing space into like regions. The advantage of this method over others is that large volumes of data are not required, as the model specifies confidence in the associations by posterior distributions. As more data is added to the model over a season, for example, the posterior distributions will change in accordance with the new data. These updates provide more confidence in the results over time, giving analysts and coaches up-to-date results which can be used to inform strategy.

7.1.2 Implications for ball and player tracking in team sports
With the growing utilisation of spatio-temporal data in team sports, the methods and findings of this thesis are applicable in team sports outside of basketball. Spatio-temporal tracking data is commonplace within numerous professional soccer leagues and football leagues, including the National Football League, Australian Football League, National Rugby League, and Super Rugby. With increased demand for player-tracking data, there is a high likelihood the financial cost associated with full player and ball tracking systems will decrease and that regulations prohibiting its use be removed at notable international competitions such as the Olympics and world cups. In all of these scenarios, measuring unpredictability of ball and player movement, and determining their association with measures of performance could provide valuable insights within these other sporting contexts.
7.1.3 **Implications for treating spatio-temporal data in sport science**

A significant finding of the current thesis was the presence of autocorrelation in spatial metrics. With the proliferation of spatial and spatio-temporal analyses in team sport from the introduction of tracking data, this is a highly relevant finding. Autocorrelation, if not accounted for, can lead to erroneous statistical findings as the assumption of independence is violated. Chapter 5 provided details on how to measure spatial autocorrelation via a Moran’s *I* test, and how to statistically analyse autocorrelated results with the Bayesian hierarchical model. This approach should be used in future research and analysis that contains spatial variables in sport.

### 7.2 Future Directions

#### 7.2.1 Investigate the nature of the association between entropy and performance

The current thesis provides considerable evidence for a link between entropy of ball movements and positive performance outcomes in women’s international basketball. However, the results are specific to the games and teams under investigation. Study 1 showed a statistically significant difference between front-court entropy between winning and losing teams and study 3 and 4 showed a strong linear relationship between the two entropy and performance measures. We do not suggest this is a general feature of basketball more broadly, therefore future research should investigate this relationship further to test if it holds among other basketball cohorts, competitions, age groups and styles of play. Accessing the vast amount of National Basketball Associations (NBA) tracking data now publicly available would be an obvious starting point. Another approach may be to more closely study what happens to the defensive team when there is high entropy vs low entropy, does the defensive structure breakdown, and if so, why? If it is not an observable breakdown, player tracking data may provide further answers to this question.
7.2.2 Investigate the phenomena across other team sports and competitions

The current conclusions are drawn from women’s international basketball, and there is some evidence of the similar results in NBA basketball and English Premier League football. Future research should continue the investigation by testing if the same relationship exists across genders and across different team sports. The way the ball and players move and use space is different across team sports and as such, the relationship cannot be assumed from investigations in other, similar sports. Furthermore, future research should investigate how age and skill level affect the use of entropy and its effects on performance. At what age/skill level is unpredictability used as a strategy in team sports? Is it difficult to execute effectively at lower skill levels? Does consciously increasing entropy of ball movements lead to negative performance outcomes at any stage?

7.2.3 Better understanding of entropy as a strategy

The current series of studies were based on questions posed by coaches who consciously wanted to play unpredictably, and hence wanted to measure and evaluate how well the strategy was being implemented. Future research should investigate if this is a common strategy, is it consciously implemented by coaches or does it more naturally emerge from the style of play, or is it something to actively avoid? A more comprehensive understanding of unpredictability in team sport strategy may lead to a better understanding of why it is used, and how effectively it is used.
7.2.4 Investigate the boundaries of the relationship

The relationship between entropy and performance has been linked to game theory in multiple studies (D’Amour, et al., 2015; Skinner, 2010; Skinner and Goldman, 2015). Future research should investigate this theoretical underpinning to explain why unpredictability is a successful strategy in team sports. Further questions that could be explored include what are the limits of unpredictability? Is there a minimum level of entropy needed before performance is negatively impacted? How long does it take to reach this minimum level; what are the boundaries of success, is there a sweet-spot, does performance plateau or degrade with increasing levels of entropy, and if so why? what conditions could allow for a team to have low entropy and still be productive? There a numerous avenue to investigate from a theoretical perspective to better understand this phenomenon.

7.3 Concluding Remarks

This thesis set out to explore ways of investigating collective behaviour in basketball that were able to add context to the traditional key performance indicators regularly collected and analysed in performance analysis; to gain a better understanding of the how and why of performance as an extension of the who, what, where, and when information. This theme was channelled through coach’s questions from the Australian women’s basketball team coaching staff to extend our understanding of performance analysis while answering practical and meaningful questions. This led to an investigation of unpredictability in basketball and its effect on performance. The thesis established a proven method for estimating unpredictability in basketball, by measuring entropy of ball movements using data that can be collected in real time with relative ease; provided a measure of spatial effectiveness, an informative and practical measure of performance previously unavailable; a statistical methodology for testing the increasing common spatial or spatio-temporal measures of performance in sports
science; and finally, compressively investigated the relationship between unpredictability and performance, comparing it to various measures of performance including effectiveness and the more precise measure of scoring efficiency. Notably, this thesis addressed gaps in the research of unpredictability in team sports, with only two studies having previously attempted to examine the relationship at the outset of this investigation.

We have shown that unpredictability is an important feature in basketball strategy, prevalent among women’s international basketball teams sampled, which could lead to significant performance benefits if instituted and executed effectively. Winning teams played with significantly higher entropy compared to teams that lost; a high probability of entropy being positively associated with spatial effectiveness regardless of spatial scale; and this relationship remained when tested with more isolated entropy and performance metrics, focusing on only the final five seconds prior to a shot.
Chapter 8 – Bibliography

CHAPTER 8.

Bibliography


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