GPS Data Analytics in Football: A Spotlight on Deceleration

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Abstract

Background: As technology has improved, the ability to gain data from player monitoring devices has become more prevalent in sport science, especially with the introduction of Global Positioning System (GPS) technology. We know that the ability to rapidly increase velocity is a key element of field-based sports such as football, which require repeated sprint efforts throughout a game. What is less intuitive is the importance of negative acceleration or “deceleration” to team-sport performance. Deceleration is important because it affords players the ability to change direction and avoid collisions. Furthermore, deceleration may be a significant contributor to muscle fatigue and damage, which is an important consideration for performance and recovery. The two predominant metrics used to describe deceleration profiles are the frequency of deceleration efforts and the distance covered whilst decelerating; however, there are flaws with both metrics when considering the deceleration movement. Similarly, as deceleration is a secondary movement to a preceding acceleration, deceleration is opportunistic and cannot be analysed in isolation.

Methods: Activity profiles were collected from twenty male football players competing in the Australian Hyundai A-League during 58 matches throughout two seasons (N = 368 observations). Match data were organised into ten 9-minute periods (i.e., P1: 0-9 min) and the time spent accelerating at moderate (1 to 2 m·s⁻²) and high (> 2 m·s⁻²) acceleration (ACC_M and ACC_H, respectively) and the time spent decelerating at moderate (-1 to -2 m·s⁻²) and high (< -2 m·s⁻²) deceleration (DEC_M and DEC_H, respectively) were quantified. Additionally, deceleration:acceleration and deceleration:high-velocity running ratios were also quantified to interrogate the opportunistic nature of deceleration activity throughout match play. A linear mixed model was used to determine the effects of time on the duration spent accelerating and
decelerating, as well as the effect of position and formation on the duration spent accelerating and decelerating.

Results: All four acceleration and deceleration metrics decreased between 23 – 26% from the first 9-min interval to the last 9-min interval. There was a significant effect of time on each metric and each displayed negative logarithmic curves within both halves of football match play. When examining the ratios of deceleration to acceleration and high-velocity running, there was no change in the ratio between DEC$_H$ duration and total acceleration duration (ACC$_H$ + ACC$_M$), while the ratios between DEC$_M$ duration and total acceleration duration, DEC$_M$ duration and high-velocity running distance (> 14.4 km·h$^{-1}$), and DEC$_H$ duration and high-velocity running distance increased as the match progressed.

Discussion: Using negative logarithmic curves to illustrate the acceleration and deceleration decay provides a novel methodological approach to quantify the high-intensity actions during football match play. The decrease in the duration of deceleration efforts throughout match play could simply be attributed to a lack of opportunity, as evident by the increase in the ratio of deceleration:acceleration and deceleration:high-velocity running. This conflicts with the conclusions of previous studies which suggest that deceleration ability is compromised in the latter periods of match play.

Practical Applications: Researchers and practitioners should consider the frequency and intensity of deceleration before making inferences regarding a decrease in a player’s ability to decelerate. By utilising negative logarithmic curves, practitioners can model the decay in acceleration and decelerations profiles. Finally, researchers and practitioners must be aware of the opportunistic nature of deceleration and monitor changes in the ratios of deceleration:acceleration and deceleration:high-velocity running, rather than relying on deceleration values in isolation.
Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Publications arising from candidature

Section 9.1 of the Griffith University Code for the Responsible Conduct of Research (“Criteria for Authorship”), in accordance with Section 5 of the Australian Code for the Responsible Conduct of Research, states:

To be named as an author, a researcher must have made a substantial scholarly contribution to the creative or scholarly work that constitutes the research output, and be able to take public responsibility for at least that part of the work they contributed. Attribution of authorship depends to some extent on the discipline and publisher policies, but in all cases, authorship must be based on substantial contributions in a combination of one or more of:

- Conception and design of the research project
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- Drafting or making significant parts of the creative or scholarly work or critically revising it so as to contribute significantly to the final output.

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- Acknowledge all those who have contributed to the research, facilities or materials but who do not qualify as authors, such as research assistants, technical staff, and
advisors on cultural or community knowledge. Obtain written consent to name individuals.

Included in this thesis is a paper in Chapter 8.0 which is co-authored with other researchers. My contribution to this paper is outlined at the front of the relevant chapter. The bibliographic details for this paper including all authors, is:

Chapter 8.0:


Appropriate acknowledgements of those who contributed to the research but did not qualify as authors are included in the paper.

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GPS Data Analytics in Football:

A Spotlight on Deceleration
Chapter 1 -

Introduction
Google searches of the words “data analytics” has increased by over 400% in the past five years (Google, 2018). Indeed, universities are tailoring Bachelor and Master degrees specifically in the study of data analytics (Australian National University, 2018; Deakin University, 2018; Griffith University, 2018). While banking, communications, government, and manufacturing have been the traditional consumers of data analytics, its application in other industries such as education, healthcare, and transportation is becoming commonplace. One such consumer that is increasingly using data to monitor the health and performance of their athletes is the sports industry, with many professional sporting clubs employing data analysts to gain an advantage over their competitors. However, for data analysts to gain any insight, valid and useful data needs to be collected to make valuable inferences.

With the increase in quality of wearable technology in elite sports, the ability to collect informative and valid data has become more efficient (Delaney, Cummins, Thornton, & Duthie, 2017). Global Positioning System (GPS) technology has enabled sport scientists to gather data on the movement patterns of elite-level athletes, with meaningful data available both live and immediately post-session. GPS has also been applied to detect the fatigue level of players during matches (Randers, 2010), identify periods of most intense match play and establish the differences in activity profiles by position, competition level, and sport (Delaney, Thornton, et al., 2017; Vigh-Larsen, Dalgas, & Andersen, 2018). As a result, there has been a growth in both the refinement and improvement of old measures of physical performance, as well as the development of new measures to progress sport science.

When describing the movement patterns of football match play, previous research has typically assessed the total distance covered, distances covered within various velocity thresholds, and the frequency of acceleration efforts (Sweeting, Cormack, Morgan, & Aughey, 2017). However, one movement pattern that is commonly overlooked is deceleration; the movement required to decrease a body’s kinetic energy or velocity (Andrews, McLeod, Ward, & Howard,
Deceleration is an important movement to consider because the ability to decrease velocity rapidly is a key element of field-based sports such as football, which require repeated high-intensity changes of direction. Football players perform, on average, 430 decelerations per match (Mara, Thompson, Pumpa, & Morgan, 2017). Furthermore, the magnitude of deceleration activity in team-sport athletes during match play has been associated with elevated circulating creatine kinase (CK) concentration, which is an estimate of the degree of muscle damage (Young, Hepner, & Robbins, 2012). Due to both the prevalence of deceleration in football match play as well as the muscle-damaging induced effects of deceleration, it is essential to interrogate the deceleration when assessing movement patterns.

When assessing deceleration, there are multiple measures to consider. The frequency of deceleration efforts gives a quick and easily interpretable measure of the amount of efforts; however, it does not describe the magnitude of the deceleration. Meanwhile, the distance covered whilst decelerating is also commonly used (Sweeting et al., 2017) due to its ability to assess the magnitude of a deceleration based on how far a player covered whilst deceleration. However, it is also inappropriate to use as it would be more beneficial for players to cover less distance while decelerating at a higher magnitude, allowing the player to turn more quickly and accelerate in the opposite direction. To decelerate, a player must have been in motion to have the opportunity to slow down. If the player had not started running, the player has no opportunity to decelerate. Therefore, when analysing the deceleration profile of a player, it must not only consider just the deceleration efforts, but also the events signifying the beginning of a sprint (i.e. acceleration and high-speed running). By developing ratios of the deceleration efforts to the acceleration efforts, these ratios demonstrate the dependency of deceleration on acceleration, and also show that the decline in deceleration could simply be attributed to a lack of opportunity.
Deceleration has only recently become a focus of analysis and therefore this thesis aimed to gain a deeper understanding of deceleration, outline the implications that deceleration monitoring can provide for clubs, and develop new metrics to analyse the data currently collected by GPS technology to provide practical applications for clubs to monitor players’ performance. The focus of this thesis is on the application of GPS data in football; specifically, quantifying the deceleration profiles of elite-level male football players during match play. Therefore, the experimental study emanating from this thesis aimed to identify a metric that could be used to describe deceleration profiles considering both the magnitude and frequency of the deceleration action.
Chapter 2 –

Review of the literature
2.1 - The use of data in sports

There are a plethora of technologies used within sport science, with devices yielding large datasets that provide great insight and understanding regarding a player’s wellbeing and movement patterns. In each data entry, limited information can be inferred or extrapolated, but collectively, across all interactions, and with the increased processing power of computers, the analysis of data has become even more powerful. However, despite the increase in the amount of data and statistical tests available, the ability to draw meaningful conclusions has been limited by the ability of sport scientists to appropriately analyse these datasets (Finch & Marshall, 2015). Paraag Marathe, president of the San Francisco 49ers, stated that “if [data] is not synthesised in a way that a QB [player] or coach can use it, then it's useless” (Brousell, 2014). In Australia, the Australian Football League is the most advanced in terms of data collection, having collected extensive data over the past 30 years (Howes, 2017); although Darren O'Shaughnessy of Ranking Software says “proper analytics have really only taken off in the past two” (Howes, 2017). Therefore, the need for appropriate analysis, not just the collection, of data is paramount within sport science in order to make meaningful inferences, with player monitoring as the main source of data within elite sports.

2.2 - Player monitoring

Player monitoring can used for the minimization of fatigue and the prevention of non-functional overreaching, illness, and/or injury (Taylor, Chapman, Cronin, Newton, & Gill, 2012). Fatigue is clearly multifactorial (Halson, 2014) and has a number of mechanisms and is appropriately described as “the failure to maintain the required or expected force (or power output)” (Edwards, 1983). From physical, psychological, mental, social or spiritual factors, a player can become “fatigued” which results in a player being unable to perform to the best of their ability during a match or training. Fatigue is typically associated with a decline in either fitness or wellbeing. If players are healthy, injury free and have low levels of fatigue, a more
consistent squad can be maintained for team selection. Furthermore, if player availability is maximised and the players in a squad are consistent, there is a higher chance of them winning against a less consistent squad (Hägglund et al., 2013). Similarly, players that complete greater than 80% of planned training weeks are seven times more likely to achieve individual performance goals (Raysmith & Drew, 2016). As a result, player monitoring is important element of sport science and conditioning within team sports.

When monitoring a player’s fitness and wellbeing, the monitoring tools fall under two broad categories: external and internal load monitors. The external load is an objective measure of the work performed by an athlete, independent of their characteristics (Wallace, Slattery, & Coutts, 2009). The internal load of a player shows the effect that the external work done has had on an athlete, whether physiological, neurological or psychological. Due to the high variability in response to exercise between players, it is not possible to understand the stress on a given player when examining the external load alone (Desgorces, Senegas, Garcia, Decker, & Noirez, 2007). Impellizzeri et al. (2004) found that when the same external load (i.e., high-speed running distances and sprinting distances) are matched by two players, the internal load differs between the players (Impellizzeri, Rampinini, Coutts, Sassi, & Marcara, 2004). Similarly, by prescribing exercise at a given intensity, the physiological response will be different among players even with the same aerobic capacity (Abt & Lovell, 2009; Bouchard & Rankinen, 2001) which could lead to some players not gaining sufficient conditioning within training sessions. Therefore, by analysing a player’s internal and external load, two conclusions can be drawn: a player’s total load (sums of internal and external loads) (Esposito et al., 2004), and a measure of fatigue (ratio between internal and external load) (Halson, 2014).
2.2.1 - Internal Load

Within internal load there are two branches: physiological load and perceptual load. Heart rate (HR) is one of the most commonly tracked metrics within sport science, and can be used to derive physiological internal load monitors (Halson, 2014; Hopkins, 1991) due to its linear relationship during steady-state exercise with the rate of oxygen consumption (Hopkins, 1991). As a result, HR can be used to categorise and prescribe exercise intensities (Borresen & Lambert, 2008). In recent years, HR-derived metrics have been developed, such as HR Variability (Buchheit, 2014) and HR Recovery (Buchheit, 2014; Daanen, Lamberts, Kallen, Jin, & Van Meeteren, 2012), to quantify aspects of the internal physiological load of a player.

When comparing perceptual internal load monitors, Rate of Perceived Exertion (RPE) is one of the more readily-used monitors due to its simplicity and cost-effectiveness. Though not entirely valid (Chen, Fan, & Moe, 2002), when RPE is used in conjunction with other measures such as Heart Rate (HR) and lactate, RPE can be a useful measure of internal load (Buchheit et al., 2013; Halson, 2014). Similarly, athlete self-reported measures (Saw, Main, & Gastin, 2016) are also commonly used perceptual internal monitoring metrics used to assess the wellbeing of a player by asking athletes to rate their mood, sleep, stress, and other wellbeing markers. Questionnaires such as the Profile of Mood States (Morgan, Brown, Raglin, O'Connor, & Ellickson, 1987), Daily Analysis of Life Demands for Athletes (Rushall, 1990), and Total Recovery Scale (Kentta & Hassmen, 1998) all provide useful subjective information to understand the wellbeing of a player (Halson, 2014).

2.2.2 - External Load

In the past, many techniques have been used to analyse the external load of players in team sports. Halson (2014) identified three subcategories: i) power output-measuring devices, ii) time-motion analysis, and iii) neuromuscular function measures, for quantifying the external
load on a player (Halson, 2014). This thesis will specifically focus on the use of time-motion analysis to quantify the acceleration and deceleration contributions to the external load of football players during match play.

2.2.3 - Match analysis techniques in sport

Two important factors when assessing the usefulness of a player monitoring tool are cost of equipment and manpower. Notational analysis, where an individual scribes every event in a match, requires minimal cost outlay but is very time consuming. Each game is subjectively coded into locomotor categories (Spencer et al., 2004), but requires many hours of manpower just to scribe a single match. Similarly, manual video analysis requires minimal cost outlay, while only one individual is required to analyse game footage. As a result, companies have developed programs to automate these processes.

Computer-based tracking systems and semi-automated tracking systems have been developed which can detect player movements and positions and produce reports like those produced via notational and manual video analysis. While products such as Prozone (Valter, Adam, Barry, & Marco, 2017) and Amisco (Castellano, Alvare-Pastor, & Bradley, 2014) drastically reduce the manpower hours required to produce reports and meaningful data, it comes at a significant outlay of which most clubs cannot justify affording. As a result, most clubs typically revert to using notational and video analysis by establishing student placements and unpaid internships as a form of gaining these manpower hours required to gain the necessary data. However, subjective analysis during notational and manual video analysis is limited by the observer’s ability to categorise high-speed movements as they are of short duration and the precision with which these are recorded is compromised. For example, an observer may categorise a sprint as when the player begins to accelerate as opposed to when they obtain a sprinting speed.
When analysing the movement patterns of athletes in field-based sports, either video-based tracking systems like the ZXY system (Bendiksen et al., 2013; Ingebrigtsen, Dalen, Hjelde, Drust, & Wisloff, 2015) or device-based tracking systems such as GPS technology are typically used. The data retrieved from GPS technology, as well as motion capture vision such as VICON can help quantify a player’s external load (Halson, 2014). Video-based tracking systems typically required larger financial outlay, as well as the requirement of setting up cameras to monitor the activity. Meanwhile GPS technology has a considerably lower financial investment and is more portable; however, requires the athlete to wear the unit.

2.3 - The global positioning system (GPS)

GPS units typically contain a GNSS receiver, an accelerometer, a gyroscope, and a magnetometer, providing a multitude of data points. GPS units contain a receiver that communicates with orbiting satellites to pinpoint the unit’s location with respect to each satellite. An accurate location for the GPS can be established if at least four satellites are in communication with the receiver (Larsson, 2003). GPS were originally designed for military use and are typically used for location purposes, with a wide variety of uses from soldiers, to vehicles, and even animals. Most commercially-available GPS technology used in sports sample at 10 Hz, resulting in 10 incoming signals each second determining the location of the unit (Cummins, Orr, O’Connor, & West, 2013). From the location signals, technology companies develop complex algorithms to derive speed and acceleration metrics based on the rate of change in 10 Hz signal (Terrier & Schutz, 2005). The speed is calculated by ‘Doppler shift’, which is the changes in satellite signal frequency due to receiver movement (Schutz & Herren, 2000). After calculating the speed, higher derivatives such as accelerations and decelerations can be calculated from the rate of change of velocity. The inbuilt accelerometer is also used by companies to develop impact-based metrics through deriving the delta accelerometer value. Similar algorithms can also be used to determine the frequency of jumps.
and dives, with some companies now developing GPS technology for specific positions in sports such as goalkeepers to measure position-specific metrics (i.e., imbalance in jump power, recovery time from dives etc.).

2.3.1 - GPS as a player tracking tool

In 1997, GPS devices were first used to detect human movement and physical activity (Schutz & Chambaz, 1997). Since then, GPS are commonly used in team sports to quantify the movement patterns of athletes during training and competition. When analysing a player’s external load, the distance covered and time spent in velocity thresholds such as jogging (approximately 7-15 km·h⁻¹), running (approximately 15-20 km·h⁻¹), high-speed running (approximately 20-25 km·h⁻¹) and sprinting (> 25 km·h⁻¹) has been predominantly employed (Bradley et al., 2009). The distance covered within these zones gives insight into the external load applied through constant and varied running; however, fails to address the changing of direction and halting, two manoeuvres that are regularly used in field-based sports. With the increase in sampling rate of GPS technologies, more appropriate measures for quantifying the load of these manoeuvres are accelerations and decelerations (Hewit, Cronin, Button, & Hume, 2011; Young et al., 2012) and therefore should be considered when measuring the external load of a player.

GPS technology has been integrated into sports due to its ability to quantify the type, duration, and frequency of discrete movements making up the intermittent-activity patterns in team sports. GPS technology can trace the movements of a player around the field and can be used to detect fatigue (Randers, 2010), identify periods of most intense play (Delaney, Thornton, et al., 2017), differentiate between activity profiles by position, competition level, and sport (Vigh-Larsen et al., 2018), and more recently to derive tactical or strategic information during match play (Aughey, 2011). Furthermore, coaches and sport scientists can periodise training
sessions from the external load performed by a player. GPS data measuring the movement patterns of match play can be used to develop sport-specific conditioning drills for training involving the movement activity, durations of movement, and rest periods that replicate the most intense periods of match play.

2.3.2 - Validity and reliability of GPS

The validity and reliability of technology is paramount when assessing whether technology can be applied for player monitoring. The first validation study with GPS technology by Edgecomb and Norton (2006) compared the total distance recorded by a 1 Hz GPS unit to the distance recorded by a trundle wheel. While the trundle wheel distance was significantly correlated to the GPS-measured distance, there was a mean error of $4.8 \pm 7.2\%$ (Edgecomb & Norton, 2006). Since this first validation study, the sampling rate of GPS technology has quickly improved, with typical commercially-available GPS technology sampling at 10 Hz. As more devices have been developed, as well as more rigorous and more complex algorithms for refining the GPS signal, the number of validation and reliability studies have increased (Aughey, 2011; Castellano, Casamichana, Calleja-Gonzalez, Roman, & Ostojic, 2011; Cummins et al., 2013; Varley, Fairweather, & Aughey, 2012). Varley et al. (2012) reported 10 Hz MiniMaxX units (Catapult Sports, Melbourne, Australia) were 2-3 times more accurate at detecting changes in velocity in comparison to 5 Hz units (Varley, Fairweather, et al., 2012). However, both the 10 Hz and 5 Hz GPS units still underestimated instantaneous velocity when compared to a 50 Hz laser (Varley, Fairweather, et al., 2012). Castellano et al. (2011) also examined the accuracy of 10 Hz MiniMaxX units and found 10 Hz units were more accurate over longer distances in comparison to previous 5 Hz GPS units (Castellano et al., 2011). A comparison study between the 10 Hz MiniMaxX units and the 15 Hz GPSports unit (GPSports, Canberra, Australia) displayed an increase in validity and inter-unit reliability in comparison to 1 Hz and 5 Hz units, and that the 10 Hz MiniMaxX unit seemed to be superior at measuring athlete movements.
However, both units are still incapable of accurately measuring movement patterns above 20 km·h\(^{-1}\) (Johnston, Watsford, Kelly, Pine, & Spurrs, 2014). Taken together, these findings suggest that an increase in sampling rate has led to an increase in validity, accuracy, and reliability of GPS units (Duffield, Reid, Baker, & Spratford, 2010; Johnston et al., 2012; Petersen, Pyne, Portus, & Dawson, 2009).

When assessing the validity and reliability of GPS technology for quantifying the acceleration and deceleration activity, Akenhead et al. (2014) established an acceleration dependent validity and reliability for 10 Hz MiniMaxX units, whereby velocity reliability and accuracy is inversely related to acceleration. Accelerations over 4 m·s\(^{-2}\) have diminished accuracy and therefore may not be appropriate in sports where athletes are regularly exceeding 4 m·s\(^{-2}\) (Akenhead, French, Thompson, & Hayes, 2014). Buchheit et al. (2014) warned against using the frequency of acceleration and deceleration efforts as some units reported up to 56% variation between units for decelerations at <-4 m·s\(^{-2}\) (Buchheit, Al Haddad, et al., 2014). However, the authors employed 15 Hz GPSSports GPS units where the 15 Hz is calculated by supplementing a 10 Hz GPS receiver with accelerometer data (Aughey, 2011), with an interpolated 5 Hz summing the total 15 Hz. While this has led to some practitioners refraining from using acceleration-derived metrics from GPS technology, it should be noted that validity and reliability studies should only be applied to the brands that are being used within the respective studies (Akenhead et al., 2014). Currently, Catapult Sports seem to be the most appropriate brand for collection due to the number of validation studies on their predecessor models (Akenhead et al., 2014; Varley, Fairweather, et al., 2012), as well as the comparisons between brands (Delaney, Cummins, et al., 2017; Johnston et al., 2014).

Delaney et al. (2017) produced a study analysing the inter-unit reliability of commonly-used acceleration and deceleration metrics, as well as the interchangeability of units across brands of GPS units (Delaney, Cummins, et al., 2017). The coefficient of variation (CV) of the number
of acceleration and deceleration efforts for the 10 Hz Catapult S5 units varied from 3.3% for low deceleration efforts to 5.9% for high acceleration efforts. The CV of the duration spent accelerating and decelerating varied from 1.6% for low deceleration to 11.8% for high deceleration, while the distance covered whilst accelerating and decelerating had a CV varying from 1.8% for low deceleration to 11.1% for high deceleration. When assessing the interchangeability between the 10 Hz Catapult S5 unit and the 5 Hz GPSports HPU unit, large differences were apparent for the number, duration and distance covered whilst accelerating, while moderate differences were evident in the number of decelerations. Finally, very large differences were reported for the duration and distance covered whilst decelerating (Delaney, Cummins, et al., 2017), which suggests that acceleration and deceleration data across different GPS brands may be comparable, but it is certainly not interchangeable.

Currently, 10 Hz is becoming the minimum sampling rate required to produce acceptable data in terms of precision and reliability with regard to total distance, distance covered in various velocity thresholds and accelerations and decelerations (Delaney, Cummins, et al., 2017). However, with the rapid development of new models and new algorithms, the rate of validity and reliability studies for each combination has not been commensurate with the recent uptake. Therefore, researchers and practitioners occasionally trust the technology that previously has been validated and found to be reliable as updates and changes to the GPS software have been implemented (Buchheit, Al Haddad, et al., 2014).

2.3.3 - Applications of GPS technology to team sports

In a similar way that coaches can utilise GPS technology for individual player monitoring, the technology can also be applied in a team context to identify styles of match play. When GPS data are aligned with notational and video analysis, coaches can identify the movement patterns as a result of differing tactics (Buchheit, Allen, et al., 2014). Coaches can identify the activity
profile both when in attack and defence, as well as where they are located on the field (i.e., front, middle, or back third). A greater understanding of the activity profile of matches and training also allows the tailoring of training to adapt players to the activity profiles required in matches. Finally, GPS technology in team sports can also be applicable for media-related purposes. By providing live data on the activity profile of players, broadcasters can create a more engaging product, enabling comparisons between players available mid-match.

2.4 - Application of GPS in football

Previously in football, GPS technology was not permitted to be worn by players in competition. As a result, the only way to describe the efforts of match was to classify the frequency of actions performed. In a typical football match, a player performs between 1000-1400 short activities in a match, requiring the player to make decisions whether to sprint, change direction, pass, or tackle every four to six seconds (Bangsbo, Norregaard, & Thorso, 1991; Mohr, Krstrup, & Bangsbo, 2003; Rienzi, Drust, Reilly, Carter, & Martin, 2000). From this information we can deduce that in a typical match, players will have 50 involvements with the ball, 30 passes, 15 tackles, and 10 headers, all of which are performed between periods of changing direction, sprinting, and monitoring team formation structure (Mohr et al., 2003).

However, more recently, players are now permitted to wear GPS technology in all levels of competition (The International Football Association Board, 2015). In the 2014 FIFA World Cup in Brazil, 905 observations of 340 players were taken across the seven rounds of the tournament (Chmura et al., 2017). A mean total distance of 10.07 ± 0.96 km per match was recorded across all players, with 8.83 ± 2.11% of the total distance covered above 19.9 km·h⁻¹. When comparing the level of competition, the total distance, percentage of total distance at high intensity, and total number of sprints were all significantly higher in semi-finals and finals in comparison to earlier matches in the knockout tournament (Chmura et al., 2017). As such,
the introduction of GPS technology has opened the scope from just classifying movements within football, to developing more specific measures of physical performance within matches. Over time, more metrics have been developed to better understand GPS data in football.

2.4.1 - Measures of physical performance

As GPS technology can quantify the type, duration, and frequency of discrete movements in team sports, researchers are constantly seeking new measures of physical performance that can be derived from this data. The total distance covered is one of the most common metrics used to quantify the external load of athletes (Sweeting et al., 2017). In football, outfield players cover between 10-12 km per match (Stolen, Chamari, Castagna, & Wisloff, 2005); however, this does not provide an appropriate representation of the match intensity. More appropriately, the distances covered within certain speed thresholds are quantified to determine the intensity of football match play (Bradley et al., 2009; Carling, Bradley, McCall, & Dupont, 2016). However, recent studies have suggested that quantifying the acceleration and deceleration profile during matches are more sensitive to fatigue than the running distance covered at different speeds (Akenhead, Hayes, Thompson, & French, 2013). Furthermore, solely quantifying the distances covered within certain speed thresholds fails to capture the moments in a match that use the most energy in a sport such as football where frequent changes of direction are prevalent (Chaouachi et al., 2012). Therefore, the quantification of an athlete’s ability to accelerate, decelerate and change direction quickly and efficiently may be more important for successful football-specific physical performance (Akenhead et al., 2013; Lockie, Murphy, Knight, & Janse de Jonge, 2011). In match play, players cover 2282 ± 120 m, 448 ± 68 m, 128 ± 29 m and 50 ± 16 m at low (0 to -1 m.s^{-2}), intermediate (-1 to -2 m.s^{-2}), high (-2 to -3 m.s^{-2}), and maximal (< -3 m.s^{-2}) deceleration intensities respectively (Osgnach, Poser, Bernardini, Rinaldo, & di Prampero, 2010). Although these values provide preliminary
information regarding the deceleration profiles of all players, these values do not consider the positional demands on deceleration frequency, distance and duration.

2.4.2 - Movement classifications

Despite the increase in studies investigating activity profiles of football players, a recent review article by Sweeting et al. (2017) outlined the need for standardisation in the classification of velocity and acceleration thresholds. As GPS technologies typically come with manufacturer-designed velocity and acceleration thresholds, many coaches are disconcerted when adjusting these values (Cunniffe, Proctor, Baker, & Davies, 2009). As a result, there is a myriad of different thresholds used to determine the velocity threshold in which an athlete is running. For example, between 0 and 5.40 m·s\(^{-1}\) has previously been classified as 'low velocity' (Varley, Gabbett, & Aughey, 2014), yet in the same sport anything greater than 4.00 m·s\(^{-1}\) has been classified as high-speed running (Sullivan et al., 2014). As such, comparison of studies that only present values within thresholds is limited unless the boundaries are aligned.

Another approach is to set thresholds as a percentage of maximal speed. For example, when setting an athlete’s maximal speed at 30 km·h\(^{-1}\), efforts between 0 – 20% (0 – 6 km·h\(^{-1}\)) would be deemed walking, 20 – 40% (6 – 12 km·h\(^{-1}\)) would be deemed jogging, 40 – 60% (12 – 18 km·h\(^{-1}\)) would be deemed running, 60 – 80% (18 – 24 km·h\(^{-1}\)) would be deemed high-speed running, and 80 – 100% (24 – 30 km·h\(^{-1}\)) would be deemed sprinting. By setting thresholds in relation to an individual’s anaerobic threshold, running speed that coincides with attainment of maximal oxygen uptake, and maximal sprinting speed, individualisation of velocity thresholds becomes much simpler for calculations, and can account for differences in physical capacity between players (Sweeting et al., 2017).
2.4.3 - Positional differences in the activity profiles of football players

As well as the need for standardisation of velocity and accelerations, the position and formation of a team can also affect the activity profiles of football players. When assessing the difference in total distance covered between positions, midfielders cover significantly higher distances than forwards or defenders (Di Salvo et al., 2007), with no significant difference between forwards and defenders. However, attackers and midfielders spend more time at high velocities than defenders (Bloomfield, Polman, & O'Donoghue, 2007). Centre midfielders (CM) cover the greatest distances in a match due to their location on the field averaging greater than 12 km per match. Meanwhile, wide players (e.g., fullbacks and wide midfielders) and forwards cover on average 11 km, while centre backs covered the smallest distance with approximately 10 km. However, these demands on positions change when assessing different speed thresholds. When examining distance covered at speeds over 19.8 km/h, wide midfielders cover the highest distance with approximately 1 km, while fullbacks, centre midfielders, and forwards cover similar distances (approximately 930 m), with central defenders significantly lower again, only covering approximately 680 m per game. With respect to acceleration and deceleration, central defenders recorded the lowest frequency of accelerations and decelerations (129 ± 6 per game) (Vigh-Larsen et al., 2018), while wide defenders and midfielders recorded the largest frequencies (180 ± 12 and 190 ± 8 per game respectively).

2.4.4 - The importance of deceleration during football

Deceleration is a crucial movement within football. Deceleration is the act of slowing down from a velocity. As with many field-based sports (hockey, rugby league etc.) the ability to slow down in football is imperative to success in the sport. In attack a player needs to evade opponents, avoid contact, and stay within bounds. In defence, a player needs to respond quickly to an opposition, whether that be by marking a player or engaging in contact to dispossess the
opposition. These movement patterns all require change of direction and, as such, require the athlete to decelerate quickly.

Deceleration is required to decrease a body’s kinetic energy \( \frac{1}{2} m \cdot v^2 \). Through deceleration, a player can halt movement or change direction. For a player to decelerate, the individual’s centre of mass (COM) needs to be posterior to their point of contact with the ground, the stiffness of joints is decreased, the flight time is minimised and the landing distance is maximised (Andrews et al., 1977). During deceleration, muscular contractions are predominantly eccentric, with contractions of the hip flexors, knee extensors and plantar flexors undergoing the most contraction (Andrews et al., 1977). It has been proposed that the eccentric contractions of the hip flexors, knee extensors and plantar flexors, during deceleration is associated with muscle damage (Andrews et al., 1977). For example, Newham et al. (1986) reported that downhill walking, which requires eccentric contractions by deceleration, is associated with significantly higher levels of plasma CK concentration, which is a marker that has been associated with muscle damage. (Newham, Jones, & Edwards, 1986). A cross-over study was performed with a 5-wk washout period, whereby participants either walked uphill (predominantly concentric contractions) or downhill (predominantly eccentric contractions) for one hour. In both conditions, heart rate, CK concentration, and the participant’s perception of pain was measured. Heart rate was significantly higher in the uphill condition, while CK concentration and perception of pain were significantly higher following the downhill condition. Even though participants felt downhill walking was virtually effortless, they were barely able to stand on their toes due to the muscle soreness and damage in the calf muscles (Newham et al., 1986). While this study was able to demonstrate that deceleration is associated with CK concentration, a more recent study reported that post-exercise CK concentration was associated with the magnitude of deceleration activity in team sport athletes (Young et al., 2012). In 2012, Young and colleagues reported that the distances covered while performing
moderate accelerations, moderate decelerations, and high decelerations during an Australian-rules football match were significantly greater for the group of players with higher post-match CK concentrations. It was found that of all commonly used GPS metrics, the distance covered below the high deceleration threshold (< -3 m·s⁻²) was the most highly correlated with post-match CK concentration. The results of this study (Young et al., 2012) suggest that high-intensity running movements in Australian-rules football match play, in particular deceleration, is a relatively large contributor to muscle damage. Given that deceleration activity is also highly prevalent in football match play (Akenhead et al., 2013; Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018), the findings from Young et al. (Young et al., 2012) also has implications for the muscle damage consequences of decelerating during football match play.

Despite the strong association between the magnitude of deceleration activity and muscle damage, deceleration is one of the least energetically-expensive movement in football (Osgnach et al., 2010). Osgnach and colleagues studied the metabolic cost of deceleration during football match play (Osgnach et al., 2010) and established that the metabolic demand at a given running speed was dependent upon the acceleration or deceleration magnitude. The least energetically-demanding deceleration magnitude was -2 m·s⁻², suggesting that decelerating at greater or less than -2 m·s⁻² is more energetically demanding for all given running velocities. Therefore, an odd conundrum has been established whereby decelerating at the relatively low intensity of -2 m·s⁻² (considered a moderate intensity deceleration) is the least energetically demanding, yet prolonged periods of decelerating is conducive to muscle damage. Due to the association between the magnitude of deceleration and a marker of muscle damage (Young et al., 2012) and the importance of a player’s ability to decelerate and change direction quickly (Akenhead et al., 2013; Lockie et al., 2011), it is necessary to explore deceleration as a physical performance measure within football.
2.5 - Methodological approaches to quantifying deceleration

The most widely used technology to quantify deceleration activity is GPS, due to the simplicity and ease of which the data can be acquired. As GPS technology is commercially sold and requires complex algorithms to calculate the data recorded, companies typically allow the user to set various velocity and acceleration thresholds so the intensity of each sprint, acceleration, and deceleration can be categorised (Witte & Wilson, 2004). Though the best practice for analysing GPS data is to preserve the continuous nature of each variable (Altman & Royston, 2006), due to the manufacturer’s software, GPS analysis is typically used with discretised zones when analysing velocities and accelerations.

Because of this discretisation, a wide variety of thresholds have been established in an attempt to categorise movements. Recently, Sweeting et al. (2017) conducted a narrative review to examine the varying velocity and acceleration thresholds employed to analyse team-sport athlete external load. (Sweeting et al., 2017). It was established that “there was no consensus on the definition of a sprint or acceleration, even within a single sport” (Sweeting et al., 2017).

For instance, the low deceleration threshold in various sports has been described as between 0 to -1 m·s⁻² (Osognach et al., 2010), between -0.65 to -1.47 m·s⁻² (Johnston, Watsford, Austin, Pine, & Spurrs, 2015), between -1 to -2 m·s⁻² (Akenhead et al., 2013) and between -1.5 to -3 m·s⁻² (Buchheit, Al Haddad, et al., 2014).

Given that deceleration is the least-energetically demanding activity, requiring less energy than constant running, and is associated with muscle damage, the quantification of deceleration activity is considered important when quantifying the athlete external load. Currently, four studies (Akenhead et al., 2013; Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018) have aimed to identify the deceleration patterns of athletes in football. These four papers are illustrated in Table 1. Akenhead et al. (2013) were the first to quantify the deceleration output
of football players within time intervals across a match (Akenhead et al., 2013). The authors quantified the distance covered accelerating across four thresholds (\(T_{\text{ACC}}, > 1 \text{ m} \cdot \text{s}^{-2}\); \(L_{\text{ACC}}, 1–2 \text{ m} \cdot \text{s}^{-2}\); \(M_{\text{ACC}}, 2–3 \text{ m} \cdot \text{s}^{-2}\); \(H_{\text{ACC}}, > 3 \text{ m} \cdot \text{s}^{-2}\)) and four levels of deceleration (\(T_{\text{DEC}}, < -1 \text{ m} \cdot \text{s}^{-2}\), \(L_{\text{DEC}}, -1 \text{ to } -2 \text{ m} \cdot \text{s}^{-2}\); \(M_{\text{DEC}}, -2 \text{ to } -3 \text{ m} \cdot \text{s}^{-2}\); \(H_{\text{DEC}}, < -3 \text{ m} \cdot \text{s}^{-2}\)).

Table 1. Review of studies analysing the transient pattern of deceleration in elite-level football

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Participants</th>
<th>Device</th>
<th>Measure</th>
<th>Time periods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Akenhead et al.</td>
<td>2013</td>
<td>36 Male players from Newcastle United (UK)</td>
<td>10 Hz MiniMaxX GPS units (Catapult)</td>
<td>- Distance covered at various deceleration thresholds</td>
<td>Six 15-min periods</td>
</tr>
<tr>
<td>Russell et al.</td>
<td>2016</td>
<td>11 Under-21 from Swansea City FC (UK)</td>
<td>10 Hz Viper Pod GPS units (STATSports)</td>
<td>- Frequency of deceleration efforts</td>
<td>Six 15-min periods</td>
</tr>
<tr>
<td>Mara et al.</td>
<td>2017</td>
<td>12 Female players from Canberra United FC (Australia)</td>
<td>8 HD video cameras imported into Optical Player Tracking System software</td>
<td>- Time between deceleration efforts</td>
<td>Six 15-min periods</td>
</tr>
<tr>
<td>Vigh-Larsen et al.</td>
<td>2018</td>
<td>14 Adult Male players and 13 U19 Male players from FC Midtjylland (Denmark)</td>
<td>ZXY tracking system</td>
<td>- Frequency of deceleration efforts</td>
<td>Six 15-min periods</td>
</tr>
</tbody>
</table>

Typically, three measures are quantified by GPS manufacturers when measuring deceleration activity: frequency, distance and duration (Cummins et al., 2013). First, the frequency of deceleration efforts illustrates the quantity of decelerations performed in a given time-period. The frequency was first reported by Russell et al. (2016) who established that there were 321 ± 38 and 291 ± 21 total decelerations (\(< -0.5 \text{ m} \cdot \text{s}^{-2}\)) in the first and second halves, respectively, in addition to 24 ± 7 and 19 ± 6 high-intensity decelerations (\(< -3 \text{ m} \cdot \text{s}^{-2}\)), respectively.
Furthermore, when examining by 15-min intervals, 116 ± 16 and 9 ± 3 total and high-intensity decelerations were reported in the first 15-min interval compared with 91 ± 10 and 6 ± 2 high-intensity decelerations (< -3 m·s⁻²) in the final 15-min of a match. Delaney et al. (2017) also found that, in rugby league, the frequency of high acceleration and deceleration efforts had the lowest association with perceived muscle soreness (Delaney, Cummins, et al., 2017) in comparison to the duration spent whilst decelerating. The frequency of efforts provide an indication of how often players are required to decelerate during football match play; however, it provides limited information on the magnitude of the deceleration efforts and the external load of each deceleration effort. Therefore, the frequency of these efforts may be inadequate to have practical implications for player monitoring. Furthermore, the act of classifying continuous data into discrete bands is both inappropriate and imprecise due to constraints applied by the GPS manufacturer (Altman & Royston, 2006).

Secondly, the distance covered whilst decelerating at a given intensity is another metric that can help to establish the deceleration activity profile. Osgnach et al. (2010) reported that football players ran 3821 ± 335 m, 1176 ± 206 m, 411 ± 98 m and 188 ± 65 m at low (0 to -1 m·s⁻²), intermediate (-1 to -2 m·s⁻²), high (-2 to -3 m·s⁻²) and maximal (< -3 m·s⁻²) deceleration intensities (Osgnach et al., 2010), which equates to 16% of total distance covered whilst decelerating at < -1 m·s⁻². These findings are similar to that of Akenhead et al. (2013), who reported that 18% of total distance is spent accelerating or decelerating (Akenhead et al., 2013). Akenhead et al. (2013) were the first to demonstrate between-half reductions in acceleration and deceleration performance, reporting significant reductions in the total deceleration distance (466 ± 42 m and 434 ± 46 m), low intensity deceleration distance (191 ± 30 m and 175 ± 29 m) moderate intensity deceleration distance (108 ± 13 m and 102 ±14 m) and high intensity deceleration distance (84 ± 17 m and 78 ± 15 m). By reporting the distance covered in each deceleration threshold, the decrease in deceleration capacity throughout a match is more
evident compared to the quantification of the frequency of deceleration efforts (Akenhead et al., 2013). However, the suggestion that the reduction in the distance covered decelerating is synonymous with a reduction in the capacity to decelerate (Akenhead et al., 2013) is not appropriate. The act of decelerating is opportunistic in nature, that is, a deceleration requires a prior acceleration and it may be that a hampered ability to accelerate, or reach peak velocity, could be masking the reduction in the distance covered while decelerating (Akenhead et al., 2013). Furthermore, the measurement of the distance covered while decelerating is counter-intuitive as it would be preferable for a player to cover a shorter amount of distance while decelerating, as it enables the player to change their direction and run in the opposite direction more easily.

Finally, the duration of time spent decelerating is another metric that can quantify the deceleration profile of an individual during match play. As GPS technology only provides the amount of time spent in discretised thresholds, the duration in each threshold provides the most appropriate measurement of deceleration (Delaney, Cummins, et al., 2017). Due to the discretised thresholds, it must be assumed that all deceleration efforts are at the lowest intensity in the given deceleration threshold (i.e., anything < -2 m·s⁻² must be assumed that it is -2 m·s⁻² as there is no way of differentiating between deceleration intensities within thresholds). As a result, a player will have accomplished a greater deceleration magnitude by spending longer decelerating at that given intensity. Given the rationale for the use of this deceleration metric, it is surprising that no previous study has reported the duration spent decelerating at various intensities as a measure of deceleration capacity.

2.5.1 - Modelling Techniques

While reporting absolute values of external load output is common within sports science literature, these values are rarely modelled to describe the changes in external load within a
match. When examining the decline in acceleration and deceleration in previous studies (Akenhead et al., 2013; Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018), it was apparent that there was a non-linear decline. As a result, a log or power analysis would be appropriate to model the decline during a match. Katz and Katz (1994) first proposed the use of log and power analyses in sports when assessing the relationship between the distance of running events and the world-record time to complete each event (Katz & Katz, 1994). From this, Delaney et al. (2017) expanded on the power law relationship to assess whether this relationship still applied to running intensity and duration of play in team sports (Delaney, Thornton, et al., 2017). It was determined that as the duration of the most intense period of football match play lengthen, the intensity of the period declines exponentially. It was also found that the rate of decline across all positions was similar, however there was positional differences in the peak running capacities achieved (Delaney, Thornton, et al., 2017). Therefore, it is reasonable to suggest that a model like that of Delaney et al. (2017) could be employed to describe the decay in high-intensity efforts (i.e., accelerations, decelerations, and high-speed running).

2.5.2 - Novel metrics

One novel metric that has been developed recently is the average acceleration metric (Delaney, Cummins, et al., 2017). This metric considers the absolute value of all acceleration and deceleration magnitudes and calculates their mean across a given period. By calculating the mean, this can be used as an indication of the intensity of the time period, of which has been found to have greater reliability between units than other threshold-based metrics (i.e., distance covered whilst accelerating or frequency of efforts) (Delaney, Cummins, et al., 2017). Similarly, an average deceleration metric could also be derived in a similar fashion only taking into consideration the deceleration magnitudes which would have the scope to further understand deceleration and acceleration profiles.
One aspect of deceleration that has never been explored is the opportunistic nature of deceleration. It is often overlooked, but it is necessary to examine as the opportunity to decelerate is complementary to high-intensity precedents (i.e., accelerating and high-speed running). That is, a deceleration can only follow from a given rate of velocity. As a result, decrements in the frequency, distance, and the duration of deceleration efforts could occur indirectly as a result of a decrease in the opportunity to decelerate and not necessarily a compromised ability to decelerate. Indeed, the reduction in the distance covered and frequency of deceleration efforts have also been accompanied with reductions in acceleration capacity and high-speed running (Vigh-Larsen et al., 2018). Furthermore, Mara et al. (2017) reported that the mean time between acceleration and deceleration efforts increased from the first half to the second half. These findings suggest that the apparent reductions in distance and magnitude of deceleration efforts (Akenhead et al., 2013; Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018) does not necessarily give causality to a compromised ability to decelerate, rather, a lack of opportunity to decelerate.

Therefore, attempts to quantify the deceleration capacity, are required to quantify the deceleration profile in relation to movements that signify the preceding actions required to create the opportunity to decelerate. Two essential metrics that should be considered in unison are the acceleration magnitude (i.e., frequency, distance, or duration) and the high-intensity velocity threshold (i.e., distance covered above a given high velocity). As a result, the development of a metric that quantifies the deceleration profile, while also accounting for the quantity of preceding high-intensity efforts the player has performed appears warranted.

2.6 – Aims and Hypotheses

The first aim of the study within this thesis is to quantify the duration spent accelerating and decelerating in elite-level football. Previous studies have quantified the frequency of
accelerations and decelerations (Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018) and the distances covered whilst accelerating and decelerating (Akenhead et al., 2013); however, no study has assessed the duration spent accelerating and decelerating. It is hypothesised that the duration spent accelerating and decelerating will more closely reflect the distances covered rather than the frequency of acceleration and deceleration efforts. From this, the second aim is to model the acceleration and deceleration profiles of elite-level male football players. As seen in the aforementioned studies (Akenhead et al., 2013; Mara et al., 2018), it is hypothesised that the time spent accelerating and decelerating will decrease as the match progresses, with an increase in activity immediately following the half-time interval. Finally, this thesis aims to establish a new metric that enhances our understanding of deceleration as an external load marker that encompasses the opportunistic nature of deceleration. Ratios of deceleration to both acceleration and high-velocity running will be established to identify whether deceleration ability is indeed compromised (Akenhead, 2013) or whether there is simply less opportunity to decelerate. It is hypothesised that there will be no change in the ratios and that a decrease in deceleration can be attributed to a lack of opportunity.
Chapter 3 –

Methods
3.1 - Subject Description

Thirty-two elite male football players registered to the same team playing in the Australian A-League participated in the study. Data was collected during the 2015/16 and 2016/17 A-League seasons. Ethics was sought from the club and approved by the Griffith University Ethics Committee (Griffith Human Research Ethics Number 2017/369). To determine the eligibility for inclusion of each player, the following criteria were satisfied: i) was aged between 18 and 40 yr, ii) had started in at least twenty matches to ensure the player is at an elite-level, and iii) had played the full 90 minutes in the match, with no injury reported before, or as a result of, the match. This excluded twelve players, with twenty players deemed eligible. The team played with three formations: 4-2-3-1, 4-2-2-2 and 4-3-3. Therefore, the players were divided into six positional groups: centre-backs (CB), fullbacks (FB), centre defensive midfielders (CDM), wingers (W), and strikers (ST). Goalkeepers were excluded from analysis as their movement demands were significantly different to the rest of the squad (data unpublished).

3.2 - Experiment Design

10 Hz Catapult X4 and S5 units (Catapult Sports) recorded the player movements of elite-level male football players across the duration of the 2015/16 and 2016/17 Australian A-League Football, FFA Cup, and Asian Champions League seasons. Twelve units were used altogether (nine X4 units and three S5 units). Due to financial constraints, the club were not able to purchase the same model of units for all of their players. Similarly, as the data was collected retrospectively, the information regarding when hardware and software updates were installed is unavailable. While this would drastically affect the effects of analysing results between players (Buchheit, Al Haddad, et al., 2014; Delaney, Cummins, et al., 2017; Thornton et al., 2018), this study aimed to investigate the within-match match change in decelerations and accelerations. Therefore, by comparing the relative change in acceleration and deceleration with respect to the first period of match play, every file has been calibrated to it’s own
hardware, software, filters, processing, and environmental conditions (i.e. satellite availability, cloud cover, stadium height etc.). While ideally the same model of unit, hardware update, and software update would be synonymous across all files, it was determined that using the delta change rather than the absolute change in acceleration and deceleration would minimise the variability associated with different hardware, software, and processing.

The units were secured in a harness, allowing the unit to sit between the scapulae of the players. The players wore the harness throughout all training sessions and therefore were familiar with the apparatus. No discomfort was reported by any athlete throughout the duration of the recording. The units were turned on and inserted into the harness of each athlete prior to the standardised warm-up before the match, allowing adequate time before the start of first half, where the pertinent data was to be recorded from. Where possible, the same unit was used for the same player each week to minimize error. The Head of High Performance monitored this process to ensure consistency in recording protocol; however, when the Head of High Performance was unable to monitor, the second most skilled worker in using GPS technology facilitated this process. The receiver for the Catapult GPS units was connected to a laptop (Asus, Beitou District, Taipei, Taiwan), and was situated just above ground level in the stadium, as per the manufacturer’s instruction. After the completion of the match, the Head of High Performance turned off all units, and uploaded the data to the laptop via a charge case (Catapult Sports). The Head of High Performance or a trained assistant coded each match in Openfield (Catapult Sports) into sections (i.e., warm-up, first half, second half, extra time if applicable), and ensured the data was coded correctly to each player. Finally, the data was uploaded to Openfield (Catapult Sports), Catapult’s encrypted storage cloud.

Consent to use the relevant data was sought from the Football Operations Manager at the Football Club. As part of the player’s contract, the club may act on behalf of the player for improvements to the player’s performance if it is delivered in a safe and effective manner. Few
risks were identified that come as a direct result of this study, however privacy of athlete’s data needed to be maintained, and therefore all data that was analysed was de-identified, with all identifiable data remaining in the Openfield software (Catapult Sports).

3.3 - Equipment

The Catapult X4 and S5 units (Catapult Sports) contained a GNSS receiver, an accelerometer and a gyroscope (Thornton, Nelson, Delaney, Serpiello, & Duthie, 2018). The GNSS receiver sampled at 10 Hz to provide location information via orbiting satellite, whilst the accelerometer and gyroscope sampled at 100 Hz to provide acceleration and inertial movement data. Distances covered at various accelerations were derived from the GNSS and accelerometer components. As the X4 and S5 units (96 x 52 x 14 mm) were only recently released before data collection, only one validity study has been published which assessed the inter-unit reliability of maximal speed during straight-line running (Delaney, Cummins, et al., 2017). However, previous studies have demonstrated the accuracy and reliability of their predecessors for the measurement of the distance covered during acceleration efforts (mean bias = −0.01 ± 0.43 m) and velocities during deceleration (mean bias = 8.9%, Pearson correlation = 0.98) (Varley, Fairweather, et al., 2012).

3.4 - Data Collection

The data for the 2015/16 and 2016/17 Hyundai A-League, FFA Cup and Asian Champions League seasons was retrieved retrospectively from Openfield (Catapult Sports). Each game file was opened consecutively and by examining the movement of players on-screen, the point of kick-off was established at the point of first player movement from the set formation for a kick-off. Similarly, the end of the half was determined by the point at which no players were deemed to be displaying actions that indicated play was continuing (i.e., pressing for the ball, moving into passing lanes etc.). While this may not be entirely accurate and congruent with the match
clock, as the analysis later to be performed only required the first 45 min of each half (i.e., no additional time), it was not deemed necessary to have the exact time of the conclusion of the half. The time of these intervals were recorded into an Excel spreadsheet for later reference when determining the intervals of each time-period. Once the playing time for each half was established, each half was broken into 9-min intervals (5 intervals + 1 for additional time each half) using the in-built function in Openfield by assigning blocks of 540 s to each half.

The following thresholds were set for accelerations:

1. A5 Acceleration containing accelerations greater than 2.0 m·s\(^{-2}\)
2. A4 Acceleration containing accelerations from 1.0 m·s\(^{-2}\) to 2.0 m·s\(^{-2}\)
3. A3 Acceleration containing decelerations and accelerations from -1.0 m·s\(^{-2}\) to 1.0 m·s\(^{-2}\)
4. A2 Acceleration containing decelerations from -1.0 m·s\(^{-2}\) to -2.0 m·s\(^{-2}\)
5. A1 Acceleration containing decelerations less than -2.0 m·s\(^{-2}\)

A comma-separated value (CSV)-format export was generated for each half with all recorded data for analysis and housed in folders according to the season and round in which the half took place.

The identity of the players who started and their playing position was established by a game log which was built in Microsoft Excel. All formation, minutes and position information were retrieved from Goal.com, Fox Sports, and Hyundai A-League website. If discrepancies occurred, the HHP determined the correct information. For this log, the starting eleven players were recorded, with the following information:

- **Player ID:** This column had a numeric value assigned for each player to de-identify the data.
- **Season:** This column indicated the season the match was played in (2015/16 or 2016/17)
- Competition: This column indicated the competition the match was played in (Hyundai A-League, FFA Cup, or Asian Champions League)

- Round: This column indicated the round of the competition the match was played in (Round 1-27, Semi-final, or Preliminary Final in HAL, Round of 32 in FFA, and Qualifier or Group match in ACL)

- Match: This column contained a unique identifier for each match that was played

- Date: This column indicated the date in which the match took place.

- Position: This was broken into seven categories: Forward (FW), Winger (W), Centre Attacking Midfielder (CAM) Centre Midfielder (CM), Centre Defensive Midfielder (CDM), Fullback (FB), and Centre Back (CB).

- Formation: There were three formations used throughout the two years:
  - 4-2-2-2 (two FB, two CB, two CDM, two W, and two FW)
  - 4-2-3-1 (two FB, two CB, two CDM, one CAM, two W, and one FW)
  - 4-3-3 Defence (two FB, two CB, two CDM, one CM, two W, and one FW)

- Side of Field: To differentiate between W, CDM, FB, and FW (only in 4-2-2-2 formation), this column indicated the side (left or right). CAM, CM, and CB were deemed to play in the middle.

- Minutes: This column indicated the number of minutes played by each player if they were substituted before the conclusion of the game.

- Full Game: This column, with reference to the minutes that were played by each player, determined whether the player completed the match.

- Location: This column indicated whether the match was held at a Home, Away, or Neutral ground.

- Opponent: This column indicated the opponent in the match.
- Result: This indicated whether the team Won, Lost, Drew, Won in Extra Time (if applicable), or Lost in Extra Time (if applicable).

In total, 726 player entries were entered into the log from 66 matches.

The game log and the CSV exports from Openfield for each half were merged and an intermediate database was built, combining all the CSV imports into one larger dataframe. To do so, a customised Python script was developed. The following steps outline the process to construct the dataframe. Please see the end of this Methods chapter for the full Python script.

1. Create a list containing the name of every CSV’s absolute path (seen in Script 1 at end of Methods chapter).
2. Establish the Season, Round and Half for each CSV from the folder the CSV files were located in (see Script 2).
3. Set formula to attach the Season, Round and Half to the CSV files (see Script 3).
4. Compile all CSV files into one main data frame (see Script 4).
5. Once the data frame of all the CSV files was compiled, a merge between the game log and the main data frame was required (see Script 5). In Catapult software, the first interval is denoted as “0”. Script 5 was used and replicated with ‘2nd Half’ inserted in the second iteration.

Following the establishment of a CSV file containing all movement data for every match entry had been established, filtering needed to occur to only house the pertinent data for the present study.

1. Full Game: Firstly, only games where the player played the full duration of the 90-minute regular time were included in the analysis. Therefore, all players who were substituted off
at some point were excluded. This was achieved by filtering out those deemed ‘Not Full Game’ in the ‘Full Game’ column.

2. Goalkeepers: Due to the vastly different positional demands, all goalkeeper entries were excluded from analysis.

3. Competition: Due to insufficient data to determine whether the competition of play was a confounding factor, only Hyundai A-League matches (the standard weekly competition) were included in the analysis.

4. Selected Metrics: While the CSV exports contained every available metric in the Catapult software, we chose to interrogate the duration spent accelerating/decelerating given the importance of these variables for the accurate quantification of football-specific physical performance. Five metrics were examined for analysis:

   1. A5 Acceleration Duration (> 2.0 m·s⁻²) coded as ACC_H
   2. A4 Acceleration Duration (1.0 m·s⁻² to 2.0 m·s⁻²) coded as ACC_M
   3. A2 Acceleration Duration (-1.0 m·s⁻² to -2.0 m·s⁻²) coded as DEC_M
   4. A1 Acceleration Duration (< -2.0 m·s⁻²) coded as DEC_H
   5. High Velocity (> 14.4 km·h⁻¹) coded as HV (used for developing ratios)

5. Extreme Outliers: To determine extreme outliers within the dataset, box-and-whisker plots were first generated to visually inspect for any obvious outliers. Erroneous values can be recorded due to lost GPS signal, and therefore the values for some metrics can become extraordinarily high, these values were to be excluded from analysis. The acceleration and deceleration data from each match were assessed for erroneous values, and any data points that lied more than four standard deviations from the local mean were removed. Of the 14,720 data points, 80 (0.54%) were deemed outliers and were excluded. Once these were
excluded, histograms and Q-Q plots were built to examine for any further abnormalities in distribution.

3.5 - Data Analysis

To visualise the data from the de-identified database, means plots were generated in Microsoft Excel 2016 (Microsoft) and SPSS V25 (IBM, Armonk, New York, United States) to illustrate the change in the duration of acceleration/decelerations throughout the 10 time-periods. These means plots highlighted a few key characteristics:

- The highest duration recorded for all four acceleration/deceleration measures was found in P1 (0:00 to 9:00 min)
- A substantial decline was seen from P1 to P2 and P3 (9:01 to 18:00 min and 18:01 to 27:00 min, respectively)
- A less severe decline/plateau was evident in P4 and P5 (27:01 to 36:00 min and 36:01 to 45:00 min respectively)
- A rapid increase was seen between P5 and P6 (45:01 to 54:00 min)
- A substantial decline from P6 to P7 and P8 (54:01 to 63:00 min and 63:01 to 72:00 min respectively)
- A less severe decline/plateau was also evident in P9 and P10 (72:01 to 81:00 min and 81:01 to 90:00 min respectively)

Due to these characteristics, it was determined that the most appropriate method to model the decay was to model the two halves independently to minimise the residuals identified in the rise between P5 and P6. Similarly, due to the sharp drops immediately after P1 and P6, and the shallower drops around P4 and P9, it was determined that linear regressions were not evident, and that either negative exponential or negative logarithmic curves more closely represented the data.
After assessing the correlation with linear, logarithmic, and exponential functions in Microsoft Excel, it was determined that negative logarithmic curves would be used to model the data due to a higher coefficient of determination. As a result, eight curves were generated for the acceleration and deceleration metrics, with two curves for each of the four metrics (one curve for each half). With these curves, two important values were quantified: a coefficient and an intercept. The coefficient was always negative to provide the decay of the curve, while the intercept was always positive to show the origin of the curve (as duration could not be negative). A more negative coefficient would indicate a sharper decay, while a less negative coefficient would indicate a less severe decay. Conversely, an intercept of a greater magnitude would indicate a larger duration to begin each half, while an intercept of a lower magnitude would indicate a smaller duration to begin each half. The coefficient of variation (CV) for each metric was calculated by dividing the average of all player means by the standard deviation of all players’ means.

As the duration values were extracted from 9-min periods of match play, pilot experimentation determined that setting the curves to bisect each 9-min period would provide the most accurate curve. Therefore, P1 was set at 4:30 min, P2 at 13:30 min, P3 at 22:50, and so forth.

3.5.1 - Opportunistic Nature of Deceleration

To determine the most appropriate metric to examine the opportunistic nature of deceleration, a ratio of deceleration to acceleration was generated as well as a ratio of deceleration to high velocity. To generate the total acceleration, the duration of high acceleration and moderate acceleration were summed to create a total acceleration metric (> 1.0 m·s⁻²) for each time period. This signified the amount of time used in that period to generate speed, and thus requiring deceleration to slow down from. Four separate ratios were constructed:

1. High deceleration duration to total acceleration duration ratio (D:A_H)
2. Moderate deceleration duration to total acceleration duration ratio (D:AM)

3. High deceleration duration to total distance covered at high velocity (D:HV_H)

4. Moderate deceleration duration to total distance covered at high velocity (D:HV_M)

These metrics were calculated in SPSS (IBM) by dividing the duration of high and moderate deceleration durations in each 9-min period respectively by the total acceleration duration and high velocity in each 9-min period that was previously calculated.

A means plot was generated to visualise the ratios. Similar to the acceleration and deceleration metrics, these ratios were tested for normality in each time period and match through visually inspecting histograms, boxplots and Q-Q plots.

3.6 - Statistical Analysis

The de-identified database was analysed using SPSS software v25 (IBM) and R Studio software (V 1.1.442). Due to functionality and ease of use, SPSS was used to generate descriptive statistics and assumption testing. For more complex modelling, R was used to develop linear mixed models (LMM) to analyse the data. Due to the dependency both within player (i.e., multiple games from the same player), as well as the dependency within game (i.e., multiple time points from the same game), it was deemed that a LMM would be the most appropriate statistical analysis test (Hopkins, Marshall, Batterham, & Hanin, 2009; Piepho, Buchse, & Richter, 2004). In the LMMs, random effects were assigned to both player and match, while fixed effects were assigned to position, formation, and interval within the match. This allowed all data points to be retained, especially when players played in different positions in different matches. Significance testing was assessed using the “stargazer” package in R software (Hlavac, 2018). Due to the rise across the half-time interval, the model was broken into three: first half, second half, and a comparison across the half-time interval.
As a result, of the 32 players, there were 20 eligible players across the following positions:

- 4 Centre Backs
- 5 Centre-Defensive Midfielders
- 2 Centre Midfielders
- 3 Full Backs
- 2 Forward
- 4 Wingers

Using the 20 eligible players, LMMs were used to test the following effects:

1. Effect of time on acceleration and deceleration metrics:
   
   **Independent Variable (IV): Interval**
   
   **Dependent Variable (DV):** $\text{ACC}_H$, $\text{ACC}_M$, $\text{DEC}_M$, and $\text{DEC}_H$
   
   **Random Effect:** Player and Match

2. Effect of time, position, and formation on acceleration and deceleration metrics:

   **IV: Interval**
   
   **Fixed Factors:** Position and Formation
   
   **DV:** $\text{ACC}_H$, $\text{ACC}_M$, $\text{DEC}_M$, and $\text{DEC}_H$
   
   **Random Effect:** Player and Match

3. Effect of time on ratio metrics:

   **IV: Interval**
   
   **DV:** $\text{D:A}_H$, $\text{D:A}_M$, $\text{D:HV}_H$, and $\text{D:HV}_M$
   
   **Random Effect:** Player and Match

The results of the LMMs were processed in Microsoft Excel for graphing and tablature.
Script 1:

```
Filenames = []

import os

for dirpath, dirnames, filenames in os.walk('~/ ***/ '):
    for file in filenames:
        if os.path.join(os.path.relpath(dirpath, '~~/ ***/'), file).endswith('.csv'):
            Filenames.append(os.path.join(os.path.relpath(dirpath, '~~/ ***/'), file))
```

Script 2:

```
def getPartsFromFilePath(filePath):
    parts = filePath.split('\
    parts[9] = parts[9][:-4]
    return parts[7:]
```

Script 3:

```
for dirpath, dirnames, filenames in os.walk('~~/ ***/ '):
    for file in filenames:
        if file.endswith('.csv'):
            appendCSV(os.path.join(os.path.abspath(dirpath),file))
```

Script 4:

```
rootDataFrame = pd.read_csv("~~/ ***/df.csv ")

def appendCSV (file_path):
    global rootDataFrame
    [year, whichRound, half] = getPartsFromFilePath(file_path)
    dataFrame = pd.read_csv(file_path,skiprows = 5, header=0)
    dataFrame["Year"] = year
    dataFrame["Round"] = whichRound
    dataFrame["Half"] = half
    rootDataFrame = rootDataFrame.append(dataFrame)
```
Script 5:

```python
j = 0
for j in Intervals:
    maskHalf = rootDataFrame['Half'] == '1st Half'
    maskInterval = rootDataFrame['Interval'] == j
    fullmask = rootDataFrame[maskHalf & maskInterval]
    df = df.merge(fullmask,how='left',left_on=['Player','Round','Year'],right_on=['Last Name','Round','Year'])
    j = j+1
df.to_csv('finaldf.csv')
```
Chapter 4 –

Results
Table 2 displays the physical performance variables to illustrate values like those previously found in literature.

### Table 2. Performance variables (mean ± SD) between first and second halves of football match play.

<table>
<thead>
<tr>
<th></th>
<th>1st Half</th>
<th>2nd Half</th>
<th>Full Match</th>
<th>95% CI Difference (H1 – H2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Distance</td>
<td>5652.3 ± 625.9</td>
<td>5245.3 ± 703.7*</td>
<td>10904.0 ± 1137.8</td>
<td>333.4 to 483.4</td>
</tr>
<tr>
<td>V4-6 (m)</td>
<td>811.9 ± 253.6</td>
<td>722.6 ± 242.3*</td>
<td>1530.6 ± 459.0</td>
<td>72.8 to 111.5</td>
</tr>
<tr>
<td>V4 (m)</td>
<td>506.5 ± 167.0</td>
<td>443.4 ± 159.1*</td>
<td>947.1 ± 303.7</td>
<td>53.2 to 77.2</td>
</tr>
<tr>
<td>V5 (m)</td>
<td>246.9 ± 95.3</td>
<td>224.4 ± 87.8*</td>
<td>469.9 ± 162.7</td>
<td>14.2 to 32.4</td>
</tr>
<tr>
<td>V6 (m)</td>
<td>58.5 ± 44.0</td>
<td>54.8 ± 43.1</td>
<td>113.6 ± 71.7</td>
<td>-1.6 to 8.9</td>
</tr>
<tr>
<td>DEC_H (n)</td>
<td>19.2 ± 7.6</td>
<td>17.0 ± 7.0*</td>
<td>36.2 ± 13.0</td>
<td>1.5 to 2.9</td>
</tr>
<tr>
<td>DEC_M (n)</td>
<td>72.8 ± 22.4</td>
<td>63.2 ± 20.5*</td>
<td>135.9 ± 40.5</td>
<td>8.1 to 11.1</td>
</tr>
<tr>
<td>ACC_M (n)</td>
<td>105.2 ± 30.9</td>
<td>91.9 ± 28.3*</td>
<td>197.1 ± 56.0</td>
<td>11.4 to 15.3</td>
</tr>
<tr>
<td>ACC_H (n)</td>
<td>21.0 ± 7.8</td>
<td>12.0 ± 5.4*</td>
<td>33.0 ± 11.6</td>
<td>8.4 to 9.8</td>
</tr>
</tbody>
</table>

N.B. V4 = 14.7 to 19.7 km·h⁻¹, V5 = 19.7 to 25.1 km·h⁻¹, V6 = > 25.1 km·h⁻¹, DEC_H = < -2 m·s⁻², DEC_M = -1 to -2 m·s⁻², ACC_M = 1 to 2 m·s⁻², ACC_H = > 2 m·s⁻², * indicates sig. different from first half (p < 0.05)

The values for all metrics except distance covered in V6 (> 25 km·h⁻¹) were significantly lower in the second half compared to the first half.

4.1 - Effect of time on acceleration and deceleration metrics

There was a significant effect of time on DEC_H (X²(9) = 273.02, p < 0.001), DEC_M (X²(9) = 736.27, p < 0.001), ACC_M (X²(9) = 952.86, p < 0.001) and ACC_H (X²(9) = 171.33, p < 0.001). Figure 1 illustrates the decay in the duration spent accelerating and decelerating throughout match play. There was a 27% decline in DEC_H from P1 to P10, a 26% decline in DEC_M, a 27% decline in ACC_M, and a 26% decline in ACC_H. In P1, players spent on average 6.7 sec (95%
CI: 5.6 to 7.9) in ACC$_H$, 38.9 sec (32.8 to 44.9) in ACC$_M$, 33.4 sec (29.2 to 37.6) in DEC$_M$, and 8.1 sec (6.5 to 9.6) in DEC$_H$. 
Figure 1. Total duration of high (top panel) and moderate (bottom panel) acceleration and deceleration efforts (ACC and DEC, respectively) during football match play. Values are mean ± 95% CI. * indicates sig. different from P1, † indicates sig. different from P5, and ^ indicates sig. different from P6.

Players spent the most time accelerating and decelerating during P1. P1 was significantly higher (p < 0.05) than all other periods in all four measures. Similarly, there was an increase following the half-time break of 8% and 6% for ACC sub H and ACC sub M, respectively, a 6% increase for DEC sub H, while there was no significant change in DEC sub M. P6 was significantly higher (p < 0.01) than P7-P10 for all measures.

Table 3. Formational effect on acceleration and deceleration metrics in elite-level football

<table>
<thead>
<tr>
<th>Measure</th>
<th>Formation</th>
<th>Difference in Mean</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACC sub H</td>
<td>4-2-2-2</td>
<td>0.302</td>
<td>(-0.278 to 0.882)</td>
</tr>
<tr>
<td></td>
<td>4-3-3</td>
<td>0.592*</td>
<td>(0.214 to 0.970)</td>
</tr>
<tr>
<td></td>
<td>4-2-2-2</td>
<td>0.446</td>
<td>(-0.150 to 1.041)</td>
</tr>
<tr>
<td></td>
<td>4-3-3</td>
<td>0.442*</td>
<td>(0.033 to 0.810)</td>
</tr>
<tr>
<td>DEC sub H</td>
<td>4-2-2-2</td>
<td>1.430</td>
<td>(-0.497 to 3.357)</td>
</tr>
<tr>
<td></td>
<td>4-3-3</td>
<td>1.872*</td>
<td>(0.631 to 3.113)</td>
</tr>
<tr>
<td></td>
<td>4-2-2-2</td>
<td>1.359</td>
<td>(-0.581 to 3.299)</td>
</tr>
<tr>
<td></td>
<td>4-3-3</td>
<td>1.717*</td>
<td>(0.468 to 2.966)</td>
</tr>
</tbody>
</table>

N.B. Reference category = 4-2-3-1 formation, * indicates significantly different from reference formation

When assessing the formational influence on the duration spent accelerating and decelerating, the 4-3-3 formation recorded significantly higher acceleration and deceleration values than the 4-2-3-1 formation, with no significant differences between the 4-2-2-2 and either 4-3-3 or 4-2-3-1 formation. The difference between formations is displayed in Table 3.
When assessing the positional influence on the duration spent accelerating and decelerating, fullbacks spent the least duration in $\text{ACC}_H$ with forwards and wingers recording significantly higher $\text{ACC}_H$ values. Centre backs were significantly lower in $\text{DEC}_H$ and $\text{DEC}_M$ than all other positions except for wingers in $\text{DEC}_M$. Centre backs also recorded the lowest $\text{ACC}_M$ values, while CDM was significantly higher than all other position except for fullbacks in $\text{ACC}_M$.

Table 4 contains the positional differences across all four measures.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Position</th>
<th>Difference in Mean</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CDM</td>
<td>0.363</td>
<td>(-0.374 to 1.100)</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>0.005</td>
<td>(-0.824 to 0.834)</td>
</tr>
<tr>
<td>$\text{ACC}_H$</td>
<td>FB</td>
<td>-0.138</td>
<td>(-0.836 to 0.560)</td>
</tr>
<tr>
<td></td>
<td>FW</td>
<td>0.861$^\sigma$</td>
<td>(-0.041 to 1.763)</td>
</tr>
<tr>
<td></td>
<td>W</td>
<td>0.715$^\sigma$</td>
<td>(-0.118 to 1.548)</td>
</tr>
<tr>
<td>$\text{DEC}_H$</td>
<td>CDM</td>
<td>1.977$^*$</td>
<td>(1.215 to 2.749)</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>1.429$^*$</td>
<td>(0.563 to 2.295)</td>
</tr>
<tr>
<td></td>
<td>FB</td>
<td>1.466$^*$</td>
<td>(0.737 to 2.195)</td>
</tr>
<tr>
<td></td>
<td>FW</td>
<td>1.582$^*$</td>
<td>(0.639 to 2.525)</td>
</tr>
<tr>
<td></td>
<td>W</td>
<td>2.150$^*$</td>
<td>(1.273 to 3.026)</td>
</tr>
<tr>
<td>$\text{ACC}_M$</td>
<td>CDM</td>
<td>3.481$^\dagger$</td>
<td>(0.902 to 6.060)</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>1.212$^\dagger$</td>
<td>(-1.620 to 4.044)</td>
</tr>
<tr>
<td></td>
<td>FB</td>
<td>2.371$^*$</td>
<td>(0.203 to 4.359)</td>
</tr>
<tr>
<td></td>
<td>FW</td>
<td>1.083$^\dagger$</td>
<td>(-1.971 to 4.137)</td>
</tr>
<tr>
<td></td>
<td>W</td>
<td>0.439$^\dagger$</td>
<td>(-2.638 to 3.516)</td>
</tr>
<tr>
<td>$\text{DEC}_M$</td>
<td>CDM</td>
<td>4.915$^*$</td>
<td>(2.375 to 7.455)</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>3.860$^*$</td>
<td>(1.077 to 6.643)</td>
</tr>
<tr>
<td></td>
<td>FB</td>
<td>2.476$^\dagger$</td>
<td>(0.345 to 4.607)</td>
</tr>
<tr>
<td></td>
<td>FW</td>
<td>3.493$^*$</td>
<td>(0.492 to 6.494)</td>
</tr>
<tr>
<td></td>
<td>W</td>
<td>1.769$^\dagger$</td>
<td>(-1.251 to 4.789)</td>
</tr>
</tbody>
</table>

N.B. Reference category = Centre Back, * indicates sig. different from CB, † indicates sig. different from CDM, $^\dagger$ indicates sig. different from CM, $^\sigma$ indicated sig. different from FB, CDM = centre defensive midfielder, CM = centre midfielder, FB = fullback, FW = forward, W = winger
From the negative logarithmic curves, a coefficient and an intercept were calculated for each measure. Table 5 displays the coefficients, intercepts, $R^2$, and coefficients of variation (CV) of the logarithmic curves.

**Table 5.** Coefficients and intercepts for the duration of acceleration and deceleration models.

<table>
<thead>
<tr>
<th></th>
<th>1st Half</th>
<th>2nd Half</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Intercept</td>
<td>$R^2$</td>
</tr>
<tr>
<td>$ACCH$</td>
<td>-0.48</td>
<td>6.39</td>
<td>0.89</td>
</tr>
<tr>
<td>$DECH$</td>
<td>-0.56</td>
<td>7.68</td>
<td>0.96</td>
</tr>
<tr>
<td>$ACCM$</td>
<td>-2.83</td>
<td>36.48</td>
<td>0.91</td>
</tr>
<tr>
<td>$DECM$</td>
<td>-1.99</td>
<td>31.88</td>
<td>0.92</td>
</tr>
</tbody>
</table>

N.B. $ACCH = $ High Acceleration, $DECH = $ High Deceleration, $ACCM = $ Moderate Acceleration, $DECM = $ Moderate Deceleration, and CV = Coefficient of Variation.

The coefficients were all lower in the second half compared to the first half; however, the intercept was of a lower magnitude. The deceleration intercepts were higher than the acceleration intercepts in the high domain, while the deceleration intercepts were lower in the moderate domain.

**4.2 - Effect of time on deceleration to acceleration ratio**

Examination of the ratios of deceleration:acceleration identified a significant increase throughout each half for $D:AM$ ($X^2(9) = 48.03, p < 0.001$), while there was no significant difference in $D:AH$ ($X^2(9) = 8.739, p = 0.462$). The ratios for each time-period are shown in Figure 2.

No significant differences were evident in $D:AH$, while $D:AM$ increased from P1 to P2 with no significant change from P2 to P5. There was a significant decrease following the half-time
break (P5 to P6) in D:A_M, with a gradual increase from P7 to P9 and a decrease in P10. The CVs for D:A_H and D:A_M were 15.3% and 5.7% respectively.

**Figure 2.** Total high (closed circles) and moderate (open circles) deceleration duration:total acceleration duration ratio during football match play. Values are Mean ± 95% CI. N.B. * indicates sig. different to P1, † indicates sig. different to P5, ^ indicates sig. different to P6. D:A_H = high deceleration:total acceleration, D:A_M = moderate deceleration:total acceleration.

### 4.3 - Effect of time on deceleration to high velocity ratio

Examination of the ratios of deceleration:high velocity identified a significant increase throughout each half for D:HV_M (X²(9) = 37.06, p < 0.001), while displaying a significant difference in D:HV_H (X²(9) = 27.151, p = 0.001). The ratios for each time-period are shown in Figure 3.

Both D:HV_H and D:HV_M were significantly lower in P1 comparative to P2 to P10. Both ratios displayed similar trends as the match progressed.
Figure 3. Total high (closed circles) and moderate (open circles) deceleration duration:high velocity distance ratio during football match play. Values are Mean ± 95% CI. N.B. * indicates sig. different to P1. D:HV_H = high deceleration:high velocity, D:AM_M = moderate deceleration:high velocity.
Chapter 5 – Discussion
The aims of this thesis were three-fold. Firstly, to quantify the duration spent accelerating and decelerating in elite-level football, secondly to model the acceleration and deceleration profiles of elite-level male football players, and finally to establish a new metric that enhances our understanding of deceleration as an external load marker that encompasses the opportunistic nature of deceleration.

5.1 - Novel Findings

5.1.1 - Quantifying the duration spent accelerating and decelerating

The present study was the first to use the duration of acceleration and deceleration efforts to describe these temporal patterns of elite-level football match play. Although the previous studies assessing the deceleration profiles of football players have provided important information regarding the deceleration output in match play, the interpretation of this data is limited due to the type of deceleration metric reported (i.e., the distance covered and frequency of acceleration and deceleration efforts). In the present study, there was an approximate 25% decline in the duration spent in all four acceleration and deceleration thresholds (DEC_H, DEC_M, ACC_M, and ACC_H) from P1 to P10. When segmented into halves, there was between 15 - 19% decline from P1 to P5 (first half), between 18 - 24% decline from P6 to P10 (second half), and between 2 - 8% increase from P5 to P6 (across the half-time interval) for all four metrics. The decline in deceleration duration is closely mirrored by the decline in acceleration, and therefore the two metrics need to be considered in tandem. Therefore, by modelling the decline in acceleration and deceleration, the synonymous values should be reflected in the decay curves.

In contrast to the previous studies, the duration spent in each deceleration band illustrates the frequency of efforts (i.e., more efforts would result in more duration spent decelerating) as well as the magnitude of deceleration effort (i.e., a deceleration from a high velocity would take longer to perform and therefore an increase in duration spent decelerating). When assessing the
distance covered whilst decelerating, ideally a player should aim to cover less distance whilst decelerating rather than more distance, as it enables a player to turn more quickly and sprint again in the opposite direction, thus increasing their chances of reaching the ball before their opponent. As such, the distance covered decelerating, should not be used as a measure of deceleration activity as it would be more beneficial for a player to cover less distance whilst decelerating. Similarly, when considering the frequency of deceleration efforts, the magnitude of these efforts is unclear, and therefore are not appropriate to identify the true deceleration profile of match play. Finally, the duration between deceleration efforts (Mara et al., 2017) fails to capture both the magnitude of each deceleration efforts, as well as the opportunistic nature of deceleration. Therefore, the duration spent decelerating is the most appropriate metric to employ.

5.1.2 - Modelling acceleration and deceleration

The second aim of this study was to use statistical modelling to illustrate the decay in a player’s ability to accelerate and decelerate within a match. Due to the half-time interval, the match was split into two negative logarithmic decay curves for all four measures (DEC_H, DEC_M, ACC_H, and ACC_M). These curves were characterised by a steep drop from P1 to P2 in the first half (P6 to P7 in second half), followed by a less severe decline from P2 to P5 (P7 to P10 in second half). Also arising from the negative logarithmic decay curves, were the coefficients and intercepts from the function of each curve. The intercept, or constant, in the decay curve illustrates the maximum capacity of the athletes for a given metric. For instance, an intercept of 7.58 in the first half for DEC_H compared to an intercept of 6.71 in the second half illustrates that the overall magnitude of deceleration output is lower in the second half comparative to the first half. This represents a 13% decline in duration spent in DEC_H during the second half in comparison to the first half. Meanwhile, the coefficient, or decay rate, illustrates the rate at which each metric declines throughout each half. A coefficient of zero would indicate no
decline at all throughout the half. This coefficient is analogous to a decrement score or a fatigue index, where the function considers the delta value from the initial time-point. For instance, in \( \text{DEC}_H \), the coefficient for the first half (-0.564) and the coefficient for the second half of -0.563 are essentially equal. This means that although the intercept is considerably lower in the second half compared to the first half, the rate at which \( \text{DEC}_H \) declines across each half is comparative. These coefficients and intercepts can be used as a method of comparing the relative acceleration and deceleration profiles of individual players and positions. Future research may obtain sufficient data for each player/position to generate valid curves and make it possible to make inferences based upon these measures to determine the capabilities of different players, and the positional demands of different formations.

5.1.3 - Ratios of deceleration to acceleration and deceleration to high-velocity running

In the present study, the novel methodology of expressing the ratios of deceleration to acceleration and ratios of deceleration to high velocity distance aimed to examine the opportunistic nature of deceleration. The \( \text{DEC}_H \) decayed at an equal rate to the total accelerations as evident by the \( \text{D:A}_H \) which did not change throughout the match. Meanwhile, the ability to decelerate in the moderate domain was better maintained despite a decay in duration spent accelerating and high velocity distance, resulting in an increase in \( \text{D:A}_M \) and \( \text{D:HV}_M \). We interpret these findings to indicate that the decline in deceleration efforts evident throughout match play could be attributed to a lack of opportunity, rather than an impaired deceleration ability. This is in opposition to the findings that suggest the ability to decelerate is hampered in the late stages of football match play (Akenhead et al., 2013; Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018). Akenhead reported reductions in the distances covered whilst accelerating and decelerating, suggesting that acceleration and deceleration capability are acutely compromised during match play (Akenhead et al., 2013). Initially, this seems valid, however there is a methodological flaw in assuming that acceleration and
deceleration are independent of each other. As deceleration requires a preceding acceleration, the ability to decelerate is heavily dependent on acceleration which makes the isolation of the deceleration profile of match playlogistically challenging to determine whether deceleration capacity is compromised. Although methodologically-flawed, the three subsequent studies assessing the deceleration profile of football match play (Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018) have all held this same assumption. The frequency of deceleration efforts does not capture the intensity of each effort (Russell et al., 2016; Vigh-Larsen et al., 2018), the duration between efforts does not capture the opportunistic nature of deceleration (Mara et al., 2017), and finally the distance covered whilst decelerating is counter-intuitive as it is more beneficial to cover less distance while decelerating, enabling a player to change direction more rapidly. This is unlike the time spent decelerating as, due to the discretised bands, the more time spent decelerating must correspond to a greater deceleration output. Therefore, the distance covered whilst decelerating, the frequency of deceleration efforts, and the duration between deceleration efforts all fail to capture elements of the deceleration profile.

In congruence with the data provided in the four previously mentioned studies examining the deceleration profile of football match play (Akenhead et al., 2013; Mara et al., 2017; Russell et al., 2016; Vigh-Larsen et al., 2018), it was apparent that all displayed similar trends between acceleration and deceleration. The reduction in the distance covered while decelerating throughout the match in the Akenhead et al. (2013) study is a close reflection of the change in distance covered while accelerating, which would presumably display no change in the ratio between deceleration and acceleration. The symmetry in the duration between deceleration efforts and the duration between acceleration efforts evident in the study of Mara et al. (2017) would also ostensibly be reflected in a constant ratio between deceleration and acceleration. Russell et al. (2016) compared the frequency of acceleration and deceleration efforts and showed the effect of time on acceleration and deceleration efforts were near identical, as seen
by partial $\eta^2$ of 0.601 and 0.603 respectively. Finally, Vigh-Larsen et al. (2018) plotted the frequency of acceleration and deceleration efforts but reported a slight increase in deceleration efforts compared to accelerations in the second 15-min interval of the match, compounding the inference that changes in deceleration values can be attributed to a lack of opportunity.

The increase in $D:A_M$ and constant $D:A_H$ could also be due to the differing energetic demands of different magnitudes of acceleration and deceleration. Moderate decelerations require the least energy of all acceleration magnitudes (Osgnach et al., 2010) and it is therefore reasonable to suggest that the least energetically-demanding movements are impacted the least throughout the duration of a match. As such, it is remiss to ignore both the magnitude of each deceleration effort (as illustrated by the duration of deceleration efforts) and the opportunistic nature of deceleration which can be identified by the ratio of deceleration to acceleration.

5.2 - Limitations of Research

This study reinforces the need to further interrogate the deceleration profile and explore different methodological approaches to understand the origin of the altered deceleration profile throughout match play. Due to varying match conditions and tactics, interpretations of the alterations in physical performance metrics should only be made on a longitudinal basis (Paul, Bradley, & Nassis, 2015). If matches are taken as standalone values, acceleration and deceleration profiles will more likely reflect the style of play in one match and are likely influenced by strategies such as athlete pacing (Paul et al., 2015), rather than a player’s impairment in a given physical performance metric. This is reflected by the coefficient of variation (CV) for each metric, with a mean CV between 6 and 14% across the four metrics. As longitudinal data is required for inferences, outputs from an individual match should not be used to draw conclusions. It should also be noted that strategies could change in the later stages.
of a match due to the match scenario, with teams needing to either protect a lead, or push for a result, which could significantly impact on the transient patterns of their activity.

One limitation of the present study is the accuracy and reliability of quantifying the acceleration and deceleration output from commercially available GPS technology (Buchheit, Al Haddad, et al., 2014). Caution needs to be taken when reporting acceleration and deceleration values due to the variability between units (Buchheit, Al Haddad, et al., 2014). To minimize the variability associated with quantifying metrics of acceleration, we quantified the relative values. By measuring changes in value, rather than absolute values, the variance attributed to the unit is reduced, thus decreasing the overall uncertainty. If the raw data was also able to be retrieved, an analysis of the exact magnitude of each deceleration effort may provide a more precise understanding of the transient nature of deceleration output. A further limitation of the present study relates to the sample size (n = 16) which was due to the stringent inclusion criteria and single pool of players (i.e., from the same team). As such, it was not feasible to generate position-specific curves. It is noted however that the acceleration and deceleration profiles may vary according to player position with wide players recording significantly more efforts than central players (Vigh-Larsen et al., 2018).

5.3 - Practical Applications

Due to the muscle damage-inducing nature of the deceleration action (Newham et al., 1986; Young et al., 2012), deceleration needs to be considered as an important part of a training program, especially where the ability to increase and decrease velocity very rapidly is a key element of performance. Modelling the decay of GPS metrics can provide practitioners with coefficients and intercepts from the negative logarithmic curves to quantify a player’s capacity and decay and can use these as markers of better conditioning. Practitioners should not view magnitude of deceleration efforts in isolation; rather, with respect to the preceding acceleration
and high-velocity running. Similarly, a ratio between deceleration and acceleration may represent a more appropriate measurement to assess the deceleration profile, as it accounts for the opportunistic nature of deceleration output during match play.

5.4 - Future Research

When exploring the deceleration profile in future studies, it is pertinent to recognise the secondary and opportunistic nature of deceleration. If the deceleration output is quantified using discretised thresholds, as seen by the typical outputs of GPS manufacturers, the duration spent in each threshold should be used, rather than the frequency of efforts or the distance covered while decelerating. If the raw GPS data is accessible, the amplitude of each deceleration effort can also facilitate an understanding of the absolute deceleration values.

When considering the change in deceleration capacity, two methods can be used. Firstly, if the discretised thresholds are quantified, values must be compared to actions signifying the start of running (i.e., an acceleration or high-speed distance). If the raw GPS data is accessible, then the change in the magnitude of decelerations throughout the duration of a match can also be used to make inferences regarding the temporal change in deceleration capacity.

In the current study, due to the limited number of players, there was not sufficient data to identify position-specific decay models. To develop position-specific models, a larger sample population would be required (n > 10 for each position) to better estimate the variance attributed to position rather than simply player variance. Similarly, having footballers play multiple positions may assist in minimising the individual variance, and increase the confidence in the position specific model of the given physical performance variable (i.e., deceleration profile). Furthermore, as this study only compared three different formations, formation-specific decay curves could also be created to highlight the highest- and lowest-acceleration and deceleration demanding formations. For instance, a 4-2-1-2 narrow formation
may demand a higher level of moderate acceleration and decelerations given the central
tendency of play, whereas a 5-4-1 wide formation may enforce more high acceleration and
deceleration efforts. Once ample coefficients and intercepts are quantified across various teams
and quality of competition, benchmarks can also be set for players to achieve appropriate player
conditioning during training, ensuring their performances are not hampered in the later stages
of a match.

Additional insights into the whole-game temporal patterns can be achieved by dividing the
periods of match play into smaller intervals. If data were divided into periods of 5 min, there
would be 18 periods throughout a match, which could identify trends that were not visible in
the 9-min intervals. For example, due to large variance there is no statistically significant
decline from P2 to P5, and from P7 to P10. Therefore, if more segmentation was used, the
difference between the 10-15 min interval and 40-45 min interval may be substantial. However,
this method may dampen the most intense period of match play as the most active period of a
match may not fall completely within one of these predefined blocks, and; therefore, the
temporal periods of match play may underestimate the activity profile of competition. The
transient changes in the deceleration profile may be more appropriately studied by employing
the use of rolling epochs (Delaney, Thornton, et al., 2017; Howe, Aughey, Hopkins, Stewart,
a rolling epoch approach, the position- and duration-specific transient decay could be illustrated
for all 90 min of the match, using a moving average method.

The establishment of the coefficients and intercepts to describe the deceleration profile of
football match play is a novel approach. As a result, this could be applied to other metrics
commonly used in GPS data analysis. I would hypothesise that total distance and distance
covered within different velocity thresholds would follow a similar trend, and that if
coefficients and intercepts could be generated for each threshold, useful practical information
could be synthesised to improve conditioning and tactical training exercises. For example, if a player has a low decay rate for velocities less than 16 km·h⁻¹ but has a high decay rate for velocities more than 16 km·h⁻¹, then more specific conditioning drills (i.e., running volume performed at velocity above 16 km·h⁻¹) can be prescribed to target the relevant deficiency.
Chapter 6 –

Conclusion
This thesis aimed to understand how GPS data has been applied in sport science, identify areas that have rarely been explored, and then translate this information into valid and meaningful metrics for player monitoring. Specifically, this thesis focused on deceleration due to the prevalence within football match play, the mechanism of the movement (i.e., muscle-damaging eccentric contractions), and the energetic demands of the movement. Three main outcomes were established: a valid metric for deceleration, a model of decay throughout football match play, and a metric to encompass the opportunistic nature of deceleration.

The duration spent whilst decelerating in discretised thresholds is available in commercially-available GPS software; however, it is rarely used. From the findings arising from this thesis, we suggest that this metric should be used to quantify the external load performed via deceleration, rather than the more commonly-used metrics such as the frequency of deceleration efforts or the total distance covered whilst decelerating.

When assessing the decay in external workload, negative logarithmic curves can be used to describe the decay, as it can be presented with a coefficient and an intercept. These decay curves, while currently only used for deceleration, can also be applied to other metrics used to quantify the external load within match play (e.g., high-speed running and metres per minute). We/I suggest that utilising a rolling epoch while calculating these values would also result in more accurate curves.

It should be known that deceleration cannot be examined independently as the action is secondary to a preceding acceleration/running velocity. Therefore, when evaluating whether an individual’s deceleration ability has been compromised, the duration spent decelerating should be compared to a primary action (e.g., the frequency and magnitude of accelerations or high-speed running). Of the data within this thesis, the rate of decay in deceleration was less
than or equal to the rate of decay in acceleration and therefore we are unable to infer that the ability to decelerate during football match play is compromised.
Chapter 7 –

References


Chapter 8 –

Submitted Manuscript
8.1 - Statement of contribution to co-authored published paper

This chapter includes a co-authored paper. The status of the co-authored paper, including all authors, is:


The contributions to the paper involved:

Timothy Newans: Idea Formation, Experimental Design, Data Analysis, Manuscript Preparation and Revisions

Phillip Bellinger: Experimental Design, Manuscript Preparation, and Revisions

Karl Dodd: Data Collection, Manuscript Preparation

Clare Minahan: Idea Formation, Experimental Design, Manuscript Preparation, and Revisions

(Signed) _________________________________ (Date)______________

Timothy Newans

(Countersigned) ___________________________ (Date)______________

Co-author of paper: Dr Phillip Bellinger

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Supervisor: Associate Professor Clare Minahan
Modelling the acceleration and deceleration profile of elite-level football players
Abstract

Purpose: The ability to increase and decrease velocity very rapidly is a key element of field-based sports such as football, which require repeated high-intensity changes of direction. The purpose of the present study was to develop a new methodological approach to quantify the acceleration and deceleration profiles of elite-level male football players during competitive match play.

Methods: Global positioning system (GPS) technology measures were collected from 20 male football players competing in the Australian Hyundai A-League during 58 matches throughout two seasons (N = 368 observations). Match data were organized into ten 9-minute periods (i.e., P1: 0 - 9 min) and the time spent accelerating at moderate (1–2 m·s⁻²) and high (>2 m·s⁻²) acceleration (ACC_M and ACC_H, respectively) and deceleration (DEC_M and DEC_H, respectively) were quantified. Additionally, deceleration:acceleration ratios were also quantified to identify the transient nature of deceleration activity throughout match play.

Results: All acceleration and deceleration metrics displayed significant negative logarithmic curves within each half of football match play, while a partial recovery was evident directly following the half-time period. There was no change in the ratio of high deceleration:acceleration; however, a significant increase in the ratio of moderate deceleration:acceleration was evident as each half progressed.

Conclusions: Using negative logarithmic curves to illustrate the acceleration and deceleration decay provides a novel methodological approach to quantify the high-intensity actions during football match play. A decrease in the duration of deceleration efforts throughout a match may be attributed to a lack of opportunity, evidenced by the increase in the ratio of deceleration:acceleration as a result of a decrease in the number of high-intensity efforts. However, improving the ability to decelerate rapidly may be an important aspect of football-specific physical performance due to the repeated high-intensity changes of direction during football match play.

Key words: GPS, player load, movement patterns, soccer
Introduction

Characterizing movement patterns and understanding the physical demands of team sports are crucial for the construction of training drills, match simulations and team strategy\(^1\)\(^-\)\(^2\). Global Positioning System (GPS) technology can be used to quantify the type, duration, and frequency of discrete movements making up the intermittent-activity patterns in team sports\(^3\)\(^-\)\(^4\). Solely quantifying the distances covered within certain speed thresholds fails to capture the moments of sports, such as football, where frequent changes of direction are prevalent\(^5\)\(^-\)\(^6\). Recent studies have suggested that quantifying the acceleration and deceleration profile during matches are more sensitive to fatigue than the running distance covered at different speeds\(^7\)\(^-\)\(^10\) which are most commonly used\(^11\)\(^-\)\(^13\). Therefore, the quantification of an athlete’s ability to accelerate and decelerate may be more important for the accurate quantification of football-specific physical performance\(^7\)\(^,\)\(^14\).

Despite the recent focus on the importance and usefulness of quantifying the acceleration profile in team-sport athletes, one metric that has been commonly overlooked is the ability to decelerate\(^11\). Indeed, decelerations are just as common as accelerations in football\(^6\) and will also contribute significantly to the players’ external load during match play. Furthermore, as decelerations are a key element in the ability to change direction\(^5\) it is vital that the deceleration profile is considered when assessing the external load of a player throughout a match. This reinforces the need to identify the typical deceleration profile during match play as a marker of physical performance for football players.

There are numerous accelerometer and GPS derived deceleration-based variables that have been used to quantify the deceleration profile of professional football match play\(^7\)\(^-\)\(^10\). For example, Akenhead et al. (2013) first reported time-dependent reductions in the total distance covered whilst decelerating\(^7\), while other research has quantified the total number of acceleration and deceleration efforts\(^8\)\(^-\)\(^10\). Alternatively, Mara et al. (2017) reported that the mean time between acceleration and deceleration efforts increased from the first half to the second half. Collectively, these studies\(^7\)\(^-\)\(^10\) have suggested that the capability to decelerate is acutely compromised during match play; however, the interpretation of some data is limited because the magnitude of the intensity of each deceleration effort was unknown in these studies\(^8\)\(^-\)\(^10\). Furthermore, the quantification of the distance covered whilst decelerating and the
number of deceleration efforts do not take into consideration whether a player has had the opportunity to decelerate. As a player’s top speed and ability to maintain speed decreases throughout a match, the opportunities to decelerate also decrease and therefore doesn’t necessarily give causality to a compromised ability to decelerate, rather, a lack of opportunity to decelerate. To consider the opportunistic nature of deceleration, the values must also be compared to a value that signifies the initiation of a sprint. Due to commercial GPS units only providing discretized values for deceleration zones, an appropriate alternative method to describe the deceleration profile is the duration spent in each deceleration zone. With a discretized value, it must be assumed that the value is at the lowest end of the zone (i.e., exactly -2.0 m·s⁻² for anything < -2.0 m·s⁻²). As a result, a player will have accomplished a greater deceleration magnitude by spending longer decelerating at that given intensity.

The present study established a ratio of deceleration:acceleration to identify the transient nature of deceleration during football match play. An increase in this ratio would imply that a player’s deceleration ability is being impeded more than their acceleration ability, whilst a decrease in this ratio would imply the opposite. Therefore, the aim of this study is to characterize the acceleration and deceleration profiles of elite footballers by quantifying the time spent in each acceleration and deceleration zone and develop a new methodological approach to minimize the bias within metrics of deceleration.

**Methods**

**Subjects**

Twenty elite male football players (age: 28.1 ± 5.3 yr, stature: 179.0 ± 7.3 cm, body mass: 74.0 ± 6.4 kg) registered to play for the same team playing in the Australian A-League were included in this study. The study was approved by the Griffith University Human Research Ethics Committee and consent was sought from the Football club to obtain the data.

**Design**
The present study used a longitudinal, observational study design utilizing data collected from 58 matches throughout the 2015/16 and 2016/17 Australia A-League seasons. For a match to be included in analysis, the football player must have played the full 90 min of the match.

**Methodology**

A total of 368 game entries were eligible (six forwards, seven midfielders and seven defenders), with a median number of games per player of 14 (Range: 5-47 matches). During each match, players wore a GPS unit which sampled at a rate of 10 Hz (Catapult X4 or S5 unit) which was turned on prior to the commencement of the warm-up (~45min prior to kick-off). Immediately prior to the warm-up each starting player was fitted with a customized harness, allowing the GPS unit to sit between the player’s scapulae. Where possible, the same unit was used for the same player each week to minimize error.

The deceleration bands were set as < -2.0 m·s⁻² for a high deceleration (DEC_H) and between -1.0 and -2.0 m·s⁻² for a moderate deceleration (DEC_M), values between -1.0 and +1.0 m·s⁻² were deemed negligible efforts and were discounted. Similarly, values between +1.0 and +2.0 m·s⁻² was deemed a moderate acceleration (ACC_M) and values greater than +2.0 m·s⁻² was deemed a high acceleration (ACC_H). These thresholds were chosen as they have been defined as moderate intensity in previous research⁷⁻⁹, thus, allowing a comparison between studies.

Data from each match was retrieved retrospectively from Catapult’s Openfield software and split into ten 9-min periods (P1 = 0-9:00 min, P2 = 9:01-18:00 min and so forth) and exported to comma-separated value format. Any additional time at the end of the regulation 45-min half was excluded from analysis for standardization. Nine minute intervals were chosen to allow each block to represent 10% worth of the match.

To analyze the data, an average duration for each acceleration and deceleration band was calculated for each player in each period to create the acceleration and deceleration profile for that player. The mean was then taken for all players for each period, from which the decay curves could be fitted. Due to the shape of decay, logarithmic functions were deemed most appropriate to estimate the decay in
each half. For each function, a coefficient and intercept were calculated. The coefficient would indicate the rate of decay for the player, of which a value of zero would indicate no decay at all. Meanwhile, the intercept would indicate the total acceleration or deceleration capacity of a player, with a higher intercept being desirable.

In order to calculate the ratio of deceleration:acceleration, the duration of DEC\textsubscript{H} and DEC\textsubscript{M} were divided by the total amount of time spent accelerating (ACC\textsubscript{H} + ACC\textsubscript{M}) in each period to generate a ratio of high deceleration:acceleration (D:A\textsubscript{H}) and a ratio of moderate deceleration:acceleration (D:A\textsubscript{M}). Similarly, the individual mean for each player in each period was calculated to quantify each player’s deceleration ratio. By calculating the mean of all players, an overall deceleration ratio was calculated for each period.

**Statistical Analysis**

The data was analyzed using SPSS V25 (IBM, Armonk, New York, United States) and using customized software (R, v 3.5.0). For statistical analysis, a linear mixed model was used to determine the effect of time on the acceleration, deceleration, and ratio measures. Chi-squared statistics and the degrees of freedom are reported in the results. The coefficient of variation (CV) for each metric was calculated by dividing the average of all player means by the standard deviation of all players’ means.

**Results**

There was a significant effect of time on DEC\textsubscript{H} (\chi^2(9) = 273.02, p < 0.001), DEC\textsubscript{M} (\chi^2(9) = 736.27, p < 0.001), ACC\textsubscript{M} (\chi^2(9) = 952.86, p < 0.001) and ACC\textsubscript{H} (\chi^2(9) = 171.33, p < 0.001). Figure 1 illustrates the decay in the duration spent accelerating and decelerating throughout match play, while Table 1 displays the coefficients, intercepts, \(R^2\), and coefficients of variation (CV) of the logarithmic curves.

Players spent the most time accelerating and decelerating during P1. P1 was significantly higher than all other periods in the first half for all four measures. There was an increase following the half-
time break of 8% and 6% for ACC<sub>H</sub> and ACC<sub>M</sub>, respectively, while there was no significant change in deceleration. P6 was significantly higher than P7-P10 for all measures.

The coefficients were all lower in the second half compared to the first half; however, the intercept was of a lower magnitude. The deceleration intercepts were higher than the acceleration intercepts in the high domain, while the deceleration intercepts were lower in the moderate domain.

Examination of the ratios of deceleration:acceleration identified a significant increase throughout each half for D:A<sub>M</sub> (X<sup>2</sup>(9) = 48.03, p < 0.001), while there was no significant difference in D:A<sub>H</sub> (X<sup>2</sup>(9) = 8.739, p = 0.462). The ratios for each time-period are shown in Figure 2.

No significant differences were evident in D:A<sub>H</sub>, while D:A<sub>M</sub> increased from P1 to P2 with no significant change from P2 to P5. There was a significant decrease following the half-time break (P5 to P6) in D:A<sub>M</sub>, with a gradual increase from P7 to P9 and a decrease in P10. The CVs for D:A<sub>H</sub> and D:A<sub>M</sub> were 15.3% and 5.7% respectively.

**Discussion**

In the present study, we identified that at both moderate and high thresholds, the time spent accelerating and decelerating displayed a negative logarithmic decay curve. The decay DEC<sub>H</sub>, DEC<sub>M</sub>, ACC<sub>M</sub>, and ACC<sub>H</sub> was similar to that of previous research<sup>7-10</sup> with large decreases from P1 to P2 and from P6 to P7 while there was a partial recovery from P5 to P6 across the half-time interval. Furthermore, there were no change in D:A<sub>H</sub> throughout match play, while D:A<sub>M</sub> increased significantly throughout each half. Collectively, these findings may indicate that the decay in deceleration may be due to a lack of opportunity rather than a compromised ability to decelerate.

The results demonstrated that after modelling the deceleration and acceleration durations, the coefficients and intercepts from the curves can appropriately quantify the decay in the durations. For instance, in ACC<sub>H</sub>, the coefficients are approximately equal (-0.48 and -0.52) for the first and second half respectively), indicating that players decay at the same rate throughout the first and second half.
Although the decay rate for ACC_H was equal throughout halves, the magnitude that the curve originated from was lower (6.39 and 5.84 for the first and second half respectively). This indicates that despite an equal decay rate, a lower magnitude of ACC_H was evident throughout the entire second half comparatively. By segmenting the matches into smaller periods (i.e., ten periods rather than six that has previously been applied\(^7\)-\(^10\)), the shape of the decay curve becomes more apparent. This may be due to the heightened motivation or strategy in P1 and P6, representing the most intense periods of match play. This could also be due to tactics\(^17\), which may mask the underlying reasons attributable to the changes in deceleration output.

In the present study, the novel methodology of expressing the ratios of deceleration to acceleration was designed to examine the opportunistic nature of deceleration. As decelerating requires a prior acceleration, it is imperative to consider deceleration in relation to acceleration. The high decelerations decayed at an equal rate to the total accelerations as seen in D:A_H. Meanwhile, the ability to decelerate in the moderate domain was maintained despite a decay in accelerating resulting in an increase in D:A_M. We interpret these findings to indicate that the decline in the deceleration duration throughout match play could be attributed to a lack of opportunity, rather than an impaired deceleration ability. This is in opposition to the findings that suggest the ability to decelerate is hampered in the late stages of football match play\(^7\)-\(^10\).

When comparing the findings of the present study with comparative literature\(^7\)-\(^10\), there is disagreement regarding the magnitude of the discrete bands employed to quantify the acceleration and deceleration output\(^11\). Two studies set >2 m·s\(^{-2}\) and <2 m·s\(^{-2}\) as their only acceleration and deceleration bands respectively\(^8,9\), another study set >3 m·s\(^{-2}\) and <3 m·s\(^{-2}\) as their high acceleration and deceleration bands\(^10\), and Akenhead et al. (2013) set six bands (three accelerations and three decelerations). Furthermore, there is currently no consensus regarding the definition of an acceleration effort which makes the comparison between studies problematic\(^11\). Therefore, due to the differences in the movement definitions and analysis techniques used in these studies\(^11\), the comparison of our research with others is difficult and should be examined with caution. Although previous studies\(^7\)-\(^10\) have provided important information regarding the deceleration profile of football match play, the interpretation of their data is
limited. For instance, ideally a player should aim to cover less distance whilst decelerating rather than more distance, as it enables a player to turn more quickly and sprint again in the opposite direction, thus increasing their chances of reaching the ball before their opponent. As a result, the distance covered whilst decelerating may not accurately reflect changes in deceleration capacity during a match. Similarly, the frequency of deceleration efforts\textsuperscript{8-10} and the duration between deceleration efforts\textsuperscript{8} have failed to capture the magnitude of these efforts and therefore are not appropriate to identify the deceleration profile of match play. Therefore, future research should utilize the duration of acceleration and deceleration efforts rather than the frequency\textsuperscript{8-10} or distance\textsuperscript{7} of these efforts. Furthermore, reporting the ratio of deceleration to acceleration can account for the opportunistic nature of deceleration.

In the present study, the D:AM increased while there was no change in the D:AH. One possible reason for these findings may relate to the energetic cost of acceleration and deceleration. Previous reports examining the energetic demands of acceleration and deceleration\textsuperscript{6} have suggested that moderate decelerations between -1.5 to -2.0 m·s\textsuperscript{-2} require the least energy of any acceleration or deceleration magnitude\textsuperscript{6}. As such, it is reasonable to suggest that the least energetically-demanding movements are affected the least throughout the duration of football match play which would explain the increase in D:AM. Similarly, when the deceleration intensity decreases below -2 m·s\textsuperscript{-2}, the associated energetic cost increases, reaching similar magnitudes compared to acceleration\textsuperscript{6}. Therefore, we suggest that the high duration of deceleration and total duration of accelerations would decay at a similar rate, resulting in no change to D:AH. As such, it is remiss to ignore the opportunistic nature of deceleration.

The present study reinforces the need to further interrogate the deceleration profile and explore different methodological approaches to understand the origin of the altered deceleration profile throughout match play, in particular, the varied responses in D:AH and D:AM. Due to varying match conditions and tactics, interpretations resulting from physical performance metrics should only be made on a longitudinal basis\textsuperscript{17}. If single matches are taken as standalone values, curves will more likely reflect the style of play in one match which are likely influenced by strategies such as athlete pacing\textsuperscript{17}, rather than a player’s impairment in match activity. This is reflected by the mean CV for DEC\textsubscript{H}, DEC\textsubscript{M}, ACC\textsubscript{M}, and ACC\textsubscript{H}, which ranged between 12 and 17\% across the four metrics. As such, we suggest that
longitudinal data (i.e., a full season of matches) is required to be able to make confident inferences about the quantification of football-specific physical performance.

One limitation of the present study relates to the accuracy and reliability of the quantification of the acceleration and deceleration output from commercially available GPS units. We used the duration of acceleration and deceleration after reviewing reliability studies as caution needs to be taken when reporting the frequency of acceleration and deceleration efforts due to the variability between units. To minimize the variability associated with quantifying metrics of acceleration, we quantified the longitudinal means and compared relative values. By measuring the delta value, rather than absolute value, the variance attributed to the unit is reduced, thus decreasing the overall uncertainty. A further limitation of the present study relates to the sample size (n = 20) which was due to the stringent inclusion criteria and single pool of players (i.e., from the same team). As such, it was not feasible to generate position-specific decay curves. However, we do acknowledge that the acceleration and deceleration profiles may vary according to player position with wide players recording significantly more efforts than central players. Further research with a larger sample size may identify position- or formation-specific decay models. Further segmentation and employing decay curves across more physical performance metrics could also add value to the GPS-derived quantification of match activity profiles.

**Practical Applications**

Deceleration needs to be considered as an important part of a training program, especially where the ability to increase and decrease velocity very rapidly is a key element of performance. Decay coefficients and intercepts from the negative logarithmic curves can be used to quantify a player’s deceleration and acceleration ability and can be implemented into current GPS analysis techniques. Similarly, a ratio between deceleration and acceleration may represent a more appropriate measurement to assess the deceleration profile, as it accounts for the opportunistic nature of deceleration output during match play.
Conclusions

The present study investigated the decline in deceleration and acceleration ability throughout the duration of elite-level football match play. The decay in deceleration and acceleration were mirrored across the high and moderate thresholds. Furthermore, there were no change in D:A_H throughout match play, while D:A_M increased significantly throughout each half. We interpret these findings to suggest that a lack of opportunity to decelerate during match play is evident, rather than a decline in deceleration ability. The decay curves presented in the current study, along with the associated coefficients and intercepts, may be used to accurately interpret a player’s acceleration- and deceleration-specific fatigue index and avoids the bias of overestimation of the effect of fatigue on the ability to decelerate.
REFERENCES


