Differences in external match load metrics between professional and semi-professional football players

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Abstract

This study aimed to investigate the differences in external match load between professional and semi-professional footballers, and also aimed to investigate whether periods of fixture congestion throughout the season had an effect on the external match load of players at either the professional or semi-professional level. This study consisted of data from 51 football players, 21 professional and 30 semi-professional footballers, playing in the 2019/2020 football season. The data collected was obtained via MEMS (micro-electromechanical systems) devices, which measured the players' total distance, high-speed distance, accelerations, decelerations and player load. Once the external match load data was quantified, a comparison between playing levels took place using a univariate ANOVA. A two-way repeated measures ANOVA was used to examine if significant differences existed in external match load variables across player performance level (2 levels) and time of the season (3 levels) during periods of time when teams experienced fixture congestion. This study found that professional players travelled significantly greater distances in a 90 minute match (10.93 ± 2.46 vs 9.02 ± 1.56 km respectively; $P<0.001$). No differences in high-speed distance were observed between playing level ($P=0.70$), whereas semi-professional players recorded significantly greater player load value than the professional players (88.6 ± 12.2 vs 68.8 ± 18.9% respectively; $P<0.001$). Periods of fixture congestion were not found to significantly affect any of the match load variables at either playing level despite the time of the season. In conclusion, neither playing level was found to exhibit a superior level of external match load. The other major finding of this thesis was that fixture congestion did not affect match load. Further research is required to quantify and compare the external match load at the non-elite professional and semi-professional level of football, as these levels of football are largely ignored in this field of literature.

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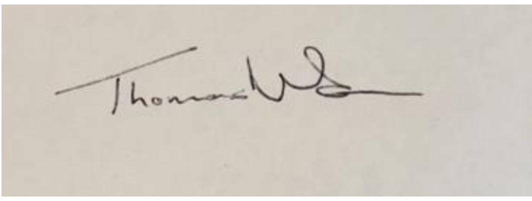
I would also like to thank John Dickinson and Brian Flynn. Their help in placing me in a good position with Faversham Town F.C was pivotal to this project. In saying that, I would also like to thank Faversham Town F.C and Gillingham F.C for allowing me to use their match data from the 2019/2020 football season.

Additional thanks go to my family and friends for their continued support throughout my academic journey which has come to a conclusion upon completion of this master's thesis.

Declaration of own work

‘No part of this thesis has been submitted in support of an application for any degree or other qualification of the University of Kent, or any other University or Institution of learning.’

Signed:



COVID-19 impact statement

Like many others, my year was heavily impacted by the coronavirus pandemic, especially with my masters' thesis. The original plan for my thesis was that I was going to collect prospective GPS data from Faversham Town F.C and run an intervention study with the football club throughout the 2020/2021 season.

However, Faversham's football season was curtailed in November 2020 due to the UK government's advice in response to COVID-19. This meant that I only had four games of data to work with and no intervention had yet taken place. At this point I had to change my thesis entirely and had to use retrospective data collected from Faversham Town's 2019/2020 season. After asking multiple football clubs to use their retrospective data to compare it to Faversham's data, Gillingham F.C gave me access to their 2019/2020 data, which I was extremely thankful of.

Unfortunately using retrospective data from two different football clubs contributed to the majority of limitations found within my study, nevertheless I am proud that I was able to overcome the difficulties associated with the coronavirus pandemic in order to produce this body of work.

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Definitions

VO_2 - volume of oxygen

VO_{2max} - maximal oxygen uptake

RPE - rating of perceived exertion

HR – heart rate

HRmax - maximum heart rate

TL – training load

ML – match load

GPS – global positioning system

CV – coefficient of variation

SEE - standard error of estimation

DEF – defenders

MID – midfielders

ATT – attackers

HSD – high speed distance

MEMS - micro-electromechanical systems

Introduction

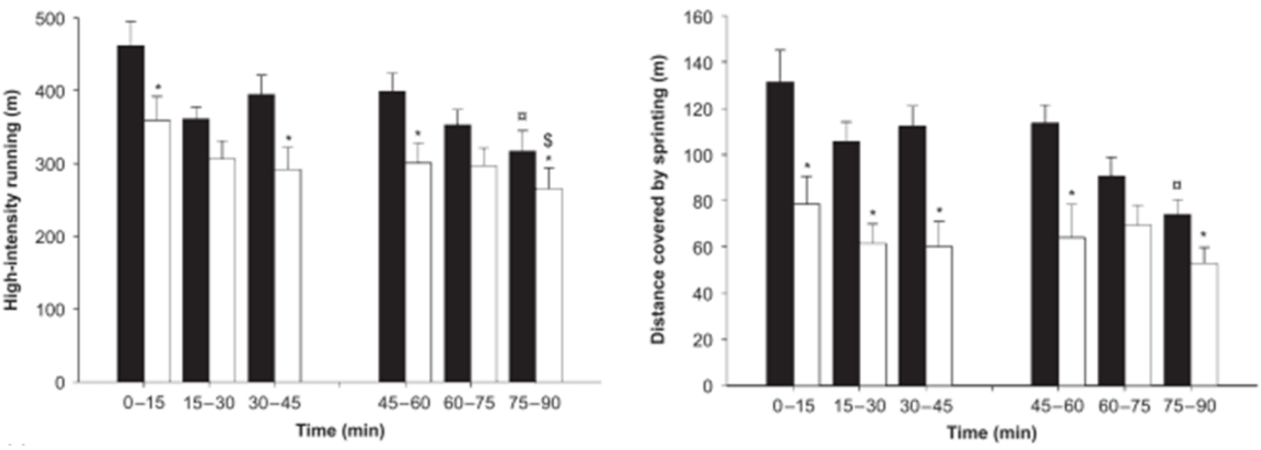
Football (also known as soccer, mainly in North America) is played in six out the seven continents on Earth and is universally regarded as the world's most popular sport (Guilianotti, 2012). The game is performed by men and women, children and adults of different cultures, classes, races and religions. An estimated 250 million people play football worldwide and it is the inclusivity of the sport that contributes to its popularity. The sport is also performed by players of different levels of playing expertise, with these levels ranging from professional to recreational with some players performing in stadiums that hold 80,000 fans and others playing in their local parks.

The popularity of football throughout the world has contributed to the demand for a scientific approach to both the preparation of players before matches and the monitoring of players performances in matches (Malone et al., 2014). The performance level of a football player depends on a multitude of factors. Technical, tactical, physical, physiological and psychological aspects are all found to affect the performance levels of a footballer (Stølen et al., 2005), with a combination of each of the factors required for elite performance. This thesis aims to specifically investigate the physical aspect of performance.

The way practitioners and sport scientists monitor the physical demands of football, often on a daily basis, is through the use of training load and match load (Impellizeri et al., 2005). Training load being the physical demands of training and match load being the physical demands of match play. Both training load and match load are specific to an individual athlete and are split into two sub-categories, which are external training/match load and internal training/match load (Impellizeri et al., 2005). External training/match load concerns the exercise quality, quantity and organisation (order of drills) and is measured by metrics such as distances travelled, running speeds and accelerations, whereas internal training/match load is the internal response to this external load and is affected by individual differences such as training status, psychological status and genetics amongst other factors. Internal load is measured by metrics such as percentage of maximum heart rate, percentage of VO_{2max} and rating of perceived exertion (RPE). Both sub-categories are important to get a comprehensive understanding of the demands of exercise.

Extensive research has been compiled quantifying the external training load of football players at the elite and sub-elite level of football (Djaoui et al., 2017; Malone et al., 2015; Wrigley et al., 2012). However, prior to 2015 FIFA (Federacion Internacional de Futbol Asociacion) had banned the use of wearable technology in competitive matches, therefore monitoring the players physical performances in match play (external match load) was limited. As a result of this, research investigating the physical performance of players in match play is also in short supply as players have only been permitted to don this wearable technology since 2015.

Whilst there is not a vast amount of research investigating the physical match demands required for football players, the literature that has been compiled suggests that different factors affect the external match load experienced by footballers (Lago et al., 2010; Mohr et al., 2003; Taylor et al., 2008). Playing position, match location, match status (winning/losing/drawing) and quality of opponent have all been found to have a significant effect on the physical demands required in match play (Lago et al., 2010; Lago & Martin, 2007; Taylor et al., 2008). Player quality has also been found to have an effect on external match load (Mohr et al., 2003), with better quality players (players playing at a higher playing level) travelling greater distances at high-speed and when sprinting than their lesser quality counterparts (as seen in figure 1).



a) *b)*

<u>*Figure 1:*</u> *High-intensity running (a) and sprinting (b) distance covered in 15-minute intervals for top-class players* ■ *and moderate players* □ *. *= Significant difference (P<0.05) between top-class and moderate players. ¤=Significantly different (P<0.05) from the first four 15 minute periods of the game. $= Significantly different from the first 15 minutes of the game. Taken from Mohr et al., (2003).*

Although, as seen above, published literature has suggested that there are factors which affect the external match load experienced by football players, the majority of this literature only focuses on the elite level of football (Lago et al., 2010; Mohr et al., 2003; Taylor et al., 2008). Even studies comparing the external match load between players of different playing qualities also only focused on the elite level, with Mohr et al., (2003) comparing external match load between elite-international players (players competing for their national teams and in the top European competitions, such as the UEFA Champions League) and elite-domestic players (players competing in the top domestic division). The results of these studies can therefore not be generalised to all the different playing levels of football, such as non-elite professional players and semi-professional footballers.

The aforementioned playing levels of football make up a large percentage of the competitive playing population, in England for example the top four leagues are professional (92 teams) of which only one (arguably two) of the divisions is regarded as elite and the semi-professional level is comprised of 296 teams. Therefore, with the lack of research quantifying the levels of external match load faced at these playing standards, the bulk of the competitive footballers are not accounted for in the published literature. Due to the number of footballers not accounted for by the published literature in this field, it is logical to suggest that research needs to be completed to gain a greater understanding of the physical demands required at the different playing standards. For this reason, the first aim of this thesis is to quantify and compare the external match load faced by players playing at the non-elite professional and semi-professional levels of football.

An issue which players have to contend with throughout the season is the rigorous fixture schedule with players often having to play at least two times a week, which means that a recovery period of 2-3 days is often all that players will have before their next fixture. The effects of residual fatigue have been found to last up to 72 hours post-match (Nédélec et al., 2012), therefore it is logical to predict that the effects of fatigue might be detrimental to a player's physical performance (external match load) in the subsequent games in times of fixture congestion. However, research has found that the physical activity and technical performance of professional players has been found to be unaffected by biweekly fixtures and times of fixture congestion (Carling et al., 2012; Dellal et al., 2015; Dupont et al., 2010), suggesting that the effects of residual fatigue do not impair the physical performance of players in times of fixture congestion.

Similar to the published research quantifying and comparing external match load between players of different qualities, the research investigating the effects of a congested fixture schedule on physical performance also has a sole focus on the elite level of football. At the non-elite professional and semi-professional levels, clubs have much less money to spend than those at the elite level. A lesser budget means that squad sizes are smaller, rest and rehabilitation facilities are worse and staff sizes are smaller, meaning that it is less likely that clubs will be able to employ an adequate number of staff members dedicated to aiding the players recovery. This means that it is logical to predict that residual fatigue is more likely to occur for players at the non-elite and semi-professional levels and that subsequent physical performance is more likely to be affected because of it. Therefore, the second aim of this thesis is to investigate whether periods of fixture congestion affect the external match load experienced by players playing at the non-elite professional and semi-professional level of football.

Literature review

Competitive football at adult level lasts 90 minutes in duration and requires energy from both the aerobic and anaerobic mechanisms to carry out the physiological demands of a football match (Bangsbo et al., 2014). The demands placed upon each player are individualised and are usually dictated by factors such as tactics, player status, opposition quality etc. (Lago & Martin, 2007). In recent years, a wealth of research has been made into football match performance (Andrzejewski et al., 2015; Mohr et al., 2003; Stølen et al., 2005) and has led to science being incorporated into the planning of training to a greater extent to prepare for the physiological demands required throughout a football match (Bangsbo et al., 2014).

Physiological Demands

Time-motion analysis research has suggested players cover a distance of 9-14 km during a 90-minute game (Barros et al., 2007; Di Salvo et al., 2007; Mohr et al., 2005; Rampinini et al., 2007). The type of exercise performed throughout a football game is intermittent in nature, with research indicating that a change in activity occurs every 4-6 seconds, therefore approximately 1330 activities take place per match (Bangsbo, 1994; Mohr et al. 2005). Players perform from 150 to 250 brief intense actions throughout the course of the 90 minutes (Mohr et al., 2003) with approximately 1,100 changes in direction of movement (Andrzejewski et al., 2015). Types of brief intense actions which occur during a game include short sprints, jumps, tackles, dual play and turning (Stølen et al., 2005). These actions along with the duration of the game suggest a strong reliance of both aerobic and anaerobic metabolism is required.

Most of the 9-14 km distance covered in a match is composed of low to moderate intensity running and walking (Bangsbo et al., 2006), therefore relying almost exclusively on aerobic metabolism with 90% of the total energy consumption throughout a match coming from aerobic metabolism (Bangsbo, 1994). Average work intensity during the 90 minutes is suggested to be between 80-85% of HRmax, with peak HR values found to reach 98% (Brewer & Davis, 1994; Helgerud et al., 2001), which is close to the anaerobic threshold of footballers. These values correspond to an average exercise intensity of approximately 75% of maximal oxygen uptake (VO_{2max}) (Astrand et al., 2003). VO_{2max} values for male professional football players are reported to vary between 55-75 $ml.kg^{-1}.min^{-1}$ (Stølen et al., 2005), such high values further amplify the notion that aerobic metabolism is frequently taxed throughout the course of a game.

Due to football match-play being unpredictable in nature, players are frequently required to perform high-intensity actions (Dupont et al., 2004). Periods of both high-intensity and low-intensity are therefore necessary throughout a game, as high-intensity activity results in an accumulation of lactate in the working muscles due to anaerobic metabolism providing energy in these bouts, with low-intensity activity necessary for recovery (Stølen et al., 2005). It is the high-intensity periods of the game which are decisive and crucial to the match outcome (Wragg et al., 2000), therefore it is clear to see that the amount of high-intensity activity possible, separates top-class players to players of a lesser standard due to their ability to influence the crucial moments more frequently. Mohr et al., (2003) found that elite domestic players performed 28% more high intensity running (2.43 vs 1.90 km; $P < 0.05$) and 58% more sprinting (650 vs 410 m; $P < 0.05$) than professional players of a lower standard. This research supports the point that top-class players are separated from players of a lesser standard by their ability to perform a greater number of high-intensity activities, thus being able to influence the crucial periods of the game more frequently.

Research has shown that high-intensity running is performed approximately every 70 seconds throughout a game, sprinting on the other hand occurs every 90 seconds, with a typical bout lasting 2-4 seconds on average (Bangsbo et al., 1991; Ekblom, 1986; Stølen et al., 2005). Earlier studies suggest that sprinting accounts for 1-11% of the total distance amassed per game (Bangsbo et al., 1991; Reilly & Thomas, 1976; Van Gool et al., 1988), however more recent literature dictates that sprinting constitutes 10% of the total distance covered during a match (Carling et al., 2008). The development in new technology, such as the employment of better-quality cameras and the introduction of GPS tracking systems allow for more accurate motion analysis, is regarded as one of the reasons for these differences in results (Carling et al., 2008; Andrzejewski et al., 2015). An alternative reason which could explain the differences in running profiles from earlier studies to more recent studies is the advancement in the tactical aspect of the game. Different tactics have been found to have significant effects on running profiles of teams and individuals (Lago et al., 2010).

Playing position and playing style have a large impact on the running profiles of footballers (Bangsbo et al., 2006). Multiple positions exist within a team, with each position imposing a different physical demand (Bloomfield et al., 2007). Several studies have investigated the difference between playing positions (Bangsbo, 1994; Ekblom, 1986; Reilly and Thomas, 1976), with Mohr et al., (2003) demonstrating that central defenders cover significantly less ground ($P<0.05$) and perform significantly less high intensity running ($P<0.05$) than midfielders, full backs and attackers (Total distance: 9.74 ± 0.22 vs. 11.00 ± 0.21, 10.98 ± 0.23, 10.48 ± 0.30 km, respectively; High-intensity running: 1.69 ± 0.10 vs. 2.23 ± 0.15, 2.46

± 0.13, 2.28 ± 0.14 km, respectively). Furthermore, full backs and attackers were found to cover significantly greater distances sprinting ($P<0.05$) than central defenders and midfielders (0.64 ± 0.06 and 0.69 ± 0.08 vs 0.44 ± 0.03 and 0.44 ± 0.04 km, respectively).

Interestingly, the results of Mohr et al. (2003) are in contrast to earlier studies of Bangsbo (1994), Ekblom (1986), and Reilly and Thomas, (1976), in so much that they suggest midfielders covered a greater distance than attackers and full backs. The differences in results between these studies and that of Mohr et al. (2003) may be explained by the development of the physical demands placed on full backs and attackers over the years (Bangsbo et al., 2006). Mohr et al., (2003) also found that all players showed a significant decline in high intensity running in the latter portion of the game, suggesting that all players, regardless of position, experience significant fatigue toward the end of a match. This is in contrast to earlier research which suggested that only midfielders experienced significant levels of fatigue towards the end of matches (Bangsbo, 1994).

As well as playing position, playing style has a significant impact on the running profiles (and thus physiological demands), of football players. Mohr et al., (2003) found significant differences within positions as well as between positions. In one game, two players in the same position displayed different running profiles, with one covering 12.3 km with 3.5 km being at high intensity, and the other 10.8 km with 2.0 km being at high intensity. These differences are likely due to different tactical roles and levels of physical capacity, suggesting that individual differences ought to be accounted for when assessing a footballer's running profile.

Situational variables must be taken into account when studying running profiles of football players. Given that football is dominated by strategic factors, it is reasonable to infer that situational variables may influence team and player match activity (Lago et al., 2010). A multitude of literature have found empirical evidence that match location (home/away), status (whether team winning/losing/drawing) and opposition quality (strong/weak) are the most important factors for performance (James et al., 2002; Jones et al., 2004; Lago & Martin, 2007; Taylor et al., 2008). However, little research exists on the impact of situational variables on physical performance during a football match, despite the recognised importance of them on match performance (Lago et al., 2010). The research that does exist suggests players perform more running at high-intensity when losing, and more low-intensity running when winning (Lago et al., 2010). However, no differences are apparent in physical performance when comparing location, suggesting the well documented 'home advantage' might be due to alternative explanations (Brown et al., 2002; Tucker et al., 2005; Neville and Holder, 1999). Lastly, the better the quality of opposition, the higher the distance covered at a lower intensity (Lago et al., 2010). These findings were similar to that of Mohr et al., (2003), who found better quality teams spent more time running at a high intensity. Therefore, it is possible to hypothesise that improving a player's/team's ability to run at a high intensity could improve the quality of the team.

Measuring and quantifying training load

Improvements in athletic performance are largely dependent on a systematic training programme (Malone, 2014). The general objectives of physical training in senior football are the ability to compete at the highest level throughout the season, and to prevent injuries (Jaspers et al., 2017). As part of efforts to minimise injuries and increase performance, many football teams employ personnel who engage in monitoring training load (TL) on a daily basis (Akenhead & Nassis, 2016). TL is the combination of training intensity, frequency & duration (Impellizeri et al., 2005), and requires manipulation in order to elicit optimal training adaptations (Malone, 2014). Training intensity is the degree of effort that is put in to complete the training session requirements, training frequency is the number of training sessions in a given period, and training duration is how long the training is performed for (Seiler & Tønnessen, 2009; Kneffel et al., 2020).

TL metrics have been divided into two sub-sections by Impellizeri et al., (2005), these being external and internal TL. External TL refers to the training prescribed by the coaches and managers, such as sets, reps, bouts of a training drill, for example, running four times 800 m at 14 km/h with 3 minutes rest in between runs, and is measured objectively often via micro-electromechanical systems (MEMS) such as GPS systems. Internal training load, on the other hand, refers to the physiological stress that the athlete experiences during training, and is commonly measured using heart rate and RPE scores (Impellizzeri et al., 2005). Match load (ML) is a part of overall TL and is similar to TL in so much that external and internal ML exist (Castillo et al., 2017), with external ML referring to measures such as distance covered, sprint distance and accelerations. Internal ML, in the same way that internal TL does, refers to the physiological stress experienced by the athlete from the match and is measured using heart rate values and RPE scores (Castillo et al., 2017).

The physiological stress induced by training or match-play stimulates physiological responses which are important to assess (Djaoui et al., 2017). Monitoring these changes are important as it gives an indication of the athlete's internal TL and ML, which means adjustments to training can be made to optimise fitness and match performance as well as avoiding excessive fatigue (Borresen & Lambert, 2008), which in turn could lead to a reduction in injury occurrence (Drew & Finch, 2016). It is important to note that the internal response to training and match play can be influenced by many factors, with current training status, age, nutritional status, previous training experience and genetic factors being examples (Bouchard & Rankinen, 2001). As such, the internal response to the same external load differs between athletes, meaning internal TL and ML ought to be considered on an individualised basis. Moreover, different individual needs are required for each football player (eg. position, formation, playing style etc.; Alexiou & Coutts, 2008), further emphasising the need for an individualised training load.

Measuring training and match loads

The validity and reliability of a measurement tool is important in the context of monitoring TL and ML, as it allows for an accurate comparison between players and sessions/matches (Macfarlane et al., 2016). Validity concerns the ability of a measurement tool to accurately measure what the tool is designed to measure (Atkinson & Nevill, 1998). The way to assess validity of a measurement tool is to compare the measurement tool in question against the gold-standard method for that particular measure (Hopkins, 2004). Atkinson & Nevill (1998) also provided a definition for reliability, as the consistency of a measurement, or of an individual's performance on a test, on repeat occasions. The reliability of a measurement tool can be calculated via multiple statistical approaches aimed at quantifying the 'within-subjects' variation, the change in the mean and the test-retest correlation (Hopkins et al., 1999). It is important to quantify both the validity and reliability of a measurement tool for a practitioner, so that the amount of error can be diminished, meaning the quality of research is better (Seale, 2004).

Advancements in modern technology, in the form of MEMS devices such as GPS technology, have meant that accurate and reliable measures of external load are possible (Coutts & Duffield, 2010). GPS is a navigation system that uses 27 operational satellites which orbit around the world (Larsson, 2003). These satellites constantly send information (at the speed of light) about time to the receiver and the exact position of the GPS system can be determined trigonometrically by the distance of the GPS system to at least four satellites (Larsson, 2003). Both distance and time are constantly measured by the GPS technology, and therefore speed of movement is able to be determined by dividing distance travelled over time taken. However, speed can also be determined by the GPS system via Doppler shift (Schutz & Herren, 2000), which is the measurements of changes in satellite signal frequency due to the movement of the receiver. Varley et al., (2012) found that 10 Hz GPS units (Catapult Minimax v4.0 10Hz) demonstrated a coefficient of variation of 2.0-5.3% at different velocities of 1 to 8 $m.s^{-1}$. Even though a sampling error exists, Varley et al., (2012) found 10 Hz GPS units to be up to six times more reliable than 5 Hz units.

As well as a coefficient of variation (CV%), data on the standard error of estimation (SEE) also exists for GPS units. CV% is the ratio of the standard deviation to the mean (higher the percentage, the larger the dispersion from the mean), whereas SEE calculates approximately how large the prediction errors are in a data set. CV% is often used to assess the reliability of GPS units (Barbero-Alvarez et al., 2010; Gray et al., 2010; Johnston et al., 2012), in contrast SEE is often used to assess the validity of GPS units (Portas et al., 2010; Varley et al., 2012). Straight line running has a SEE of 2.6% in the Catapult Minimax v2.5 5Hz GPS unit, whereas multi-directional running with turns between 45-180 degrees has a SEE of up to 6.8% (Portas et al., 2010). Turns and multi-directional running are common in football, with approximately 1,100 changes in direction of movement occurring over a 90-minute match (Andrzejewski et al., 2015), therefore it is logical to predict that a SEE of up to 6.8% occurs throughout football matches if using the Catapult Minimax v2.5 5Hz GPS unit.

Due to differences in manufacturer, latitude, sampling rate, methodology and statistical analysis, a global statement on the validity and reliability of GPS units for measuring team sports movements is not possible (Akenhead et al., 2014). Therefore, an abundance of research has been compiled in order to determine the most accurate and reliable model of GPS unit at measuring team sport specific movements (Castellano et al., 2011; Scott et al., 2016; Varley et al., 2012;).

Differences in sampling rate have been found to have a great effect on the reliability and validity of GPS units (Castellano et al., 2011; Varley et al., 2012; Jennings et al., 2010). An increase in the reliability of the units were found to coincide with an increase in sampling rate, with Jennings et al., (2010) finding improved reliability and accuracy when comparing GPS unit with a sampling rate of 5 Hz (Catapult Minimax v2.5 5Hz) to one with a sampling rate of 1 Hz (GPSports™ SPI Elite 1Hz). Castellano et al., (2011) reported a further improvement occurred when comparing a 10 Hz unit (Catapult Minimax v4.0 10Hz), to the two used in the study by Jennings et al., (2010). This was further emphasised by two research studies: that of Varley et al., (2012), which as previously mentioned found that a 10 Hz GPS unit (Catapult Minimax v4.0 10Hz) was up to six times more reliable than a 5 Hz unit (Catapult Minimax v2.5 5Hz), and that of Malone (2014). Malone (2014) found low CV% values (0.6-1.5) when using 10 Hz GPS units (SPI Pro X, GPSports™, Canberra, Australia), in contrast previous research has found high CV% values (>10%) at sampling frequencies of 1 Hz (Jennings et al, 2010) and 5 Hz (Coutts & Duffield, 2010). Scott et al., (2016) however found no additional benefits to using a sampling frequency of 15 Hz. Therefore, it is logical to suggest that a sampling frequency of 10 Hz improves the accuracy and reliability of monitoring sport specific movements.

The validity of GPS units has also been found to be influenced by sampling frequency (Varley et al., 2012). Varley et al., (2012) found that a 10 Hz GPS unit (V4.0 MinimaxX) was two to three times more accurate than a 5 Hz unit (V2.0 Minimaxx) and also dictated that the 10 Hz units produced sufficient accuracy to quantify acceleration, deceleration and constant velocity in a team sport environment. Scott et al., (2016) further emphasised this, compiling a review of 22 studies examining the validity and reliability of GPS units. This review found that all GPS units are reliable at tracking distance, however 10 Hz GPS units were found to be the most valid and reliable at tracking team sport simulated running. Good (<5%) to moderate (5-10%) reliability and validity measures were reported for 10 Hz units, overcoming limitations of earlier models and performing better than 15 Hz models.

Although GPS units with a sampling rate of 10 Hz have been found to be more accurate and reliable than those sampling at lower and higher rates, validity and reliability issues still exist. Research by Akenhead et al., (2014) found that the accuracy and reliability of GPS units (Catapult S4 10 Hz model) is compromised at accelerations exceeding 4 $m.s^{-1}$ (SEE=0.32 $m.s^{-1}$). This was further emphasised by research by Rampinini et al., (2015), which found good accuracy for the GPS when measuring total distance and high-speed running (CV% of 1.9 and 4.7%, respectively) but poor accuracy when measuring very high-speed running (>5.56 $m.s^{-1}$; CV% of 10.5). From these studies it is clear to see that the GPS units have some limitations when players are travelling at top end speed, with the accuracy and reliability of the units worsening as speeds reach very high levels. As a result of this, practitioners need to be aware of the GPS error associated with these high speeds (>5.56 $m.s^{-1}$) and take it into account when interpreting and making decisions based on the GPS data. Additionally, literature has suggested that practitioners should assign the same MEMS unit to the same athlete for every use, so that inter-unit variation is eliminated (Scott et al., 2016; Akenhead et al., 2014). Inter-unit variation concerns the consistency of the measurements between the same units from the same manufacturer. Scott et al., (2016) found inter-unit variation between every MEMS unit when reviewing units with sampling rates of 1 Hz, 5 Hz, 10 Hz and 15 Hz respectively. Therefore, assigning a MEMS unit to each athlete to wear every time is important as it is the only way of eliminating inter-unit variation.

Modern MEMS devices also include triaxial accelerometers as well as the GPS technology (Krasnoff et al., 2008). Triaxial accelerometers measure movement in three planes (longitudinal, anterior-posterior and mediolateral) and the sum of these three accelerations produces a composite vector magnitude, which is expressed as G-force (Macfarlane et al., 2016). This therefore means that accelerometers can quantify measures such as playerload™ (later explained), as the triaxial system collates all of the forces acting on the player. Accelerometers sample at a rate of 100 Hz (Beanland et al., 2014), which is far greater than the GPS devices offer, therefore devices equipped with accelerometers offer higher sampling rates than devices without (Boyd et al., 2011). Boyd et al., (2011) also found accelerometers (MinimaxX 2.0, Catapult Innovations, Victoria) to have acceptable levels of reliability both between and within devices.

MEMS data had been previously only used to monitor external training load, with FIFA not permitting players to wear external devices in competitive match play. However, as previously mentioned, in 2015 FIFA overturned this decision, allowing the use of wearable technology in competition. This has meant that MEMS technology has become more attractive to practitioners, with them being able to monitor both external TL & ML (Rago et al., 2020).

There is no gold standard measure for quantifying external match load. Therefore, a range of variables, which can be measured by MEMS devices during match play, have been used to quantify external match load. Variables such as total distance, distance per minute, peak speed, energy expenditure and arbitrary speed zones amongst many other variables (as shown in figure 1) have been used in research to assess external match load (Rago et al., 2020). Rago et al. (2020) conducted a systematic review on the methods of collecting and interpreting external load and 32 of the 34 studies used arbitrary speed zones to quantify external load, which was by far the most popular variable used to interpret external load. These zones are used to distinguish between distance run at low-intensity, medium-intensity and high-intensity and these zones are differentiated by velocity thresholds (Malone et al., 2014). Low-intensity running/walking is generally classified as distance travelled below the speed of 7 km/h and medium-intensity running/jogging is generally classified as distance travelled between 7-13 km/h (Clemente et al., 2019; Jaspers et al., 2018). High-intensity running is generally classified as distance travelled above the speed of 14.4 km/h (Scott et al., 2013; Silva et al., 2017; Thorpe et al., 2015). High-speed running has been commonly preferred as an indicator for an athlete's external load due to it being easily measurable as well as research dictating that a greater involvement of neuromuscular components are associated with increasing running speed (Kyröläinen et al., 2005).

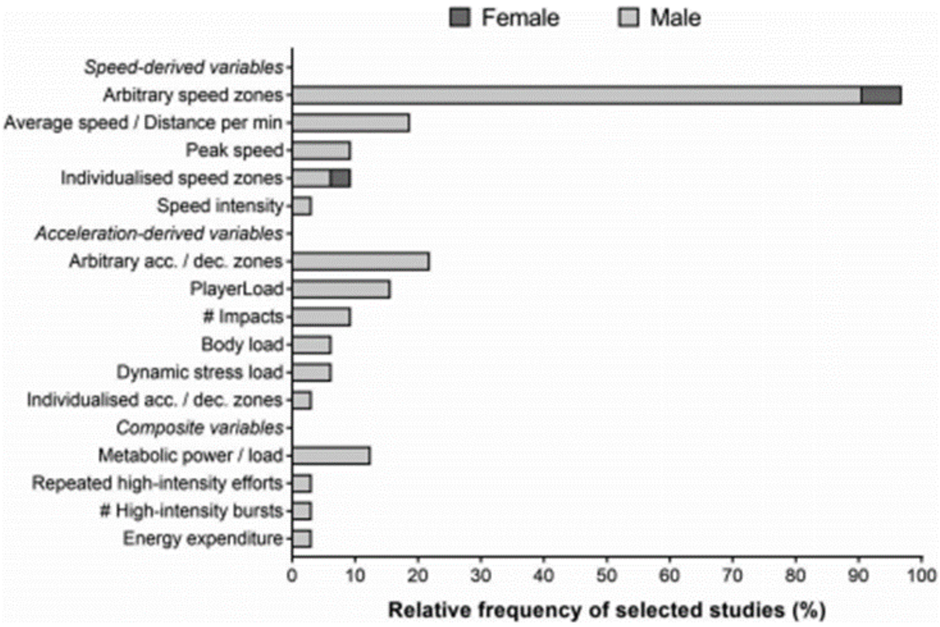


Figure 2: Frequency of variables adopted in studies monitoring external training load using microtechnology incorporating global positioning systems in professional football players. Total distance not included in figure as every study used this metric. Taken from literature review by Rago et al., (2020).

Multiple studies have also incorporated subzones of high-speed running, for example very high-speed running and sprinting, to provide a more detailed portfolio of an athlete's external load (Rago et al., 2020). Very high-speed running concerns distance covered between 19.8-25.2 km/h, whereas sprinting refers to distance covered exceeding 25.2 km/h (Abbot et al., 2018; Buchheit et al., 2016; Malone et al., 2018). It is important to note that these speed zones are not consistent throughout every piece of research in this field, however the speed zones above are the most popular zones used throughout the literature according to the systematic review of Rago et al. (2020). Whilst these arbitrary speed zones are extremely popular in the research concerning the quantification of external load, they have drawn criticism for not providing information regarding the relative intensity at which an athlete is working (Hunter, Bray & Towlson, 2015). The internal response to the same external demand varies between athletes due to factors mentioned above, such as current fitness status of players, previous training experience, and genetic factors (Bouchard & Rankinen, 2001). This variance between an athlete's internal response to the same external load is further emphasised by research monitoring athletes of different ages and maturity levels (Gabbett, 2015).

Individualised speed zones have been introduced as an alternative to arbitrary speed zones (Abbott et al., 2018; Abt & Lovell, 2009, Hunter, Bray & Towlson, 2015). Abt and Lovell (2009) compared distance run at high-intensity during football matches using an absolute speed threshold of 19.8 km/h, and an individualised high-intensity speed threshold based on the speed amassed at the second ventilatory threshold. This study found significant differences in high-intensity distance run between the absolute speed threshold (845 m) and the relative speed threshold (2258 m), suggesting that the use of absolute speed thresholds may significantly underestimate the high-intensity running during match play. Despite this evidence, arbitrary speed thresholds are still more common in recent literature (Rago et al., 2020) and systems such as ProZone (ProZone Sports Ltd. ®, Leeds, UK) and Playertek™ (Catapult Sports®, Melbourne, Australia) that are commonly used by professional sports teams both use arbitrary speed zones to monitor high-intensity running.

Measuring running distance at high speed as an external load metric does not take into account the effort made when changing to another speed (Rago et al., 2020), therefore monitoring accelerations and decelerations are important in order to assess the external load of an athlete. Accelerations are more energetically demanding than running at constant velocity (Rampinini et al., 2007) and are demonstrated to occur 3-8 times more frequently than sprints. Decelerations are just as common as accelerations in football (Osgnach et al., 2010), therefore also contribute to the overall external, and internal, match load. A study by Dalen et al., (2016) found that accelerations contribute to 7-10% of external match load, whereas decelerations contribute to 5-7%. In the same way as high-speed running distance, a limitation for the use of accelerations and decelerations as a metric to monitor external load is that they do not consider speed as a variable affecting external load. Consequently, it would be rational to suggest that a combination of the two variables would provide for a more comprehensive measurement of external load.

Whilst running distance at high speed (using speed zones) has traditionally been used as a key external load metric, the introduction of triaxial accelerometers has enabled MEMS devices to measure variables such as player impacts (significant events that exclude footsteps during walking and running) and 'Playerload™' (Boyd et al., 2011). Playerload™ (originally developed by the Australian Institute of Sport as a metric to measure effort) is the root mean square of the squared instantaneous rate of change of acceleration in each of the three vectors and divided by 100 (Colby et al., 2014). Playerload™ has been proposed as an alternative method to monitor an athlete's external load, with Barrett et al., (2014) finding Playerload™ to have moderate to high test-retest reliability and that it is able to effectively monitor external load during intermittent and multidirectional running (Barrett et al., 2014).

In spite of this, few studies have explored composite variables as a way to monitor external load (Gaudino et al., 2015; Martin-Garcia et al., 2018; Silva et al., 2017). Research conducted by Gaudino et al., (2013) attempted to combine both of the variables discussed in the previous paragraph (accelerations/decelerations and speed) to obtain a more comprehensive estimation of external load via the means of measuring the athlete's metabolic power. Metabolic power was calculated by multiplying energy cost of accelerated running on grass - an equation proposed by di Pampero et al., (2005) by running speed at any given time (i.e., every 0.2 seconds). Gaudino et al., (2013) found that traditional methods to measure external load (high speed running) underestimated the true value of external load and suggested that metabolic power was more accurate representation of an athlete's external load.

Effect of fatigue on external match load

External load and recovery time have an important relationship, as an imbalance between the two, over time, can lead to effects associated with overtraining such as residual fatigue (Nimmo & Ekblom, 2007). Fatigue is defined as the failure to maintain the required or expected power output (Edwards, 1983). Footballers experience two types of physical fatigue; acute fatigue (experienced for less than three hours post-match play and also during match play during high-intensity periods of the game or late in the game) and residual fatigue (experienced for up to 72 hours post-match with longer periods needed to recover) (Mohr et al., 2005; Silva et al., 2013). Both acute and residual fatigue can result in performance decrements in the few days following a game (Ispirlidis et al., 2008). Therefore, being able to monitor the fatigue status of individuals would be advantageous for a football club so that diminishing performance levels can be minimised, especially during periods of fixture congestion.

In terms of acute fatigue, studies have shown that the amount of sprinting, high-intensity running and total distance covered are significantly lower in the second half of a match compared to the first half (Bangsbo, 1994; Bangsbo et al., 1991; Reilly & Thomas, 1976). This could suggest that performance decrements occur in the second half and fatigue may be present towards the end of a game. This was further emphasised by research by Mohr et al., (2003), who found that the amount of high intensity running was significantly reduced in the last 15 minutes of a game, as well as finding that over 40% of players experienced their least intense period of the game over this time.

Acute fatigue has also been found to occur in the opening exchanges of the second half (Mohr et al., 2005). However, the physiological mechanisms responsible for this fatigue are suggested to be different to the mechanisms responsible for the fatigue experienced in the latter stages of the game. According to Mohr et al., (2005) fatigue experienced in the opening exchanges of the second half may be due to markedly reduced muscle temperature as a result of the half time period, whereas fatigue amassed nearing the end of the game may be due to a depletion of muscle glycogen in the exercising muscles, as well as dehydration and hyperthermia.

Monitoring acute fatigue during the game could be advantageous for football clubs as it can guide strategic use of substitutes and can therefore reduce the effects of fatigue across the team as a whole (Reilly et al., 2008). Whilst substitutions are also made for tactical reasons, it has been found that substitutes that were brought on before 75 minutes showed superior work-rate in the last 15 minutes of a game than those who had played the entirety of the game (Mohr et al., 2005). This research further supports the notion that monitoring acute fatigue throughout the game can be advantageous to football teams, as strategies can be adopted to counter the effects of fatigue across the entire team.

Residual fatigue, in contrast to acute fatigue, implies that longer periods of time are required to fully recover post-exercise (Silva et al., 2018). In football, post-match fatigue has many potential causes, with dehydration, glycogen depletion, muscle damage and mental fatigue being the four most heavily researched causes (Nédélec et al., 2012). The effects of this residual fatigue have been found to be detected for up to 72 hours after a match (Nédélec et al., 2012), with both sprint performance and jump performance being frequently used as recovery markers in the days after a match (Andersson et al., 2008; Ispirlidis et al., 2008; Magalhães et al., 2010). These studies have found that sprint performance can be up to 5% impaired even after 72 hours post-match, and jump performance affected by up to 10%. The findings of these studies suggest it is important to monitor the fatigue markers post-match, especially when fixtures are biweekly (two games a week) so that the effects of fatigue can be reduced.

In modern football the ability to recover from match play and intense training is considered to be a major determinant of subsequent performance (Mohr et al., 2005). Professional and semi-professional players often encompass biweekly fixtures throughout the course of a season, which means a recovery period of 2-3 days is often all that players will have before their next fixture. It is logical to think that performance will be impaired in the subsequent game due to the effects of residual fatigue lasting up to 72 hours post-match. However, the physical activity and technical performance of professional players has been found, in an abundance of studies, to be unaffected by biweekly fixtures and times of fixture congestion (Carling et al., 2012; Dellal et al., 2015; Dupont et al., 2010). This therefore suggests that the effects of residual fatigue are not apparent for professional players when competing in times of fixture congestion, with no significant differences in physical and technical performance occurring from match to match in these times of congestion. Explanations for these findings have been proposed such as player rotation and regulation of movement by players with the knowledge that they have a secondary fixture in the coming days (Carling et al., 2012).

The research by Carling et al., (2012), Dellal et al., (2015) and Dupont et al., (2010) all investigate the effects of residual fatigue on professional football players, therefore this research cannot be generalised for footballers competing at different levels, for example the semi-professional level. At the semi-professional level, a lesser budget means that squad sizes are smaller; therefore rotation of players isn't as easy as it is at the professional level, meaning that it is logical to predict residual fatigue is more likely to occur for players at the semi-professional level.

As well as not accounting for semi-professional players, the research by Carling et al., (2012), Dellal et al., (2015) and Dupont et al., (2010) does not represent the majority of professional footballers, as all three research papers investigate players and teams playing in the UEFA Champions League (the most elite European club competition). These studies cannot be generalised therefore, to neither semi-professional players nor non-elite professional players. No studies to date, to the authors knowledge, have examined the effects of a congested fixture schedule has on the external match load of non-elite professional football players and semi-professional football players.

Furthermore, in the same way players experience different levels of external load, they will also experience different levels of internal load (Bouchard & Rankinen 2001). Therefore, it is important to note that recovery is individualised and although the research by Carling et al., (2012), Dellal et al., (2015) and Dupont et al., (2010) suggests that residual fatigue is not apparent for professional players in times of fixture congestion, the fatigue status of the players should be observed on an individual basis and subsequent loads adjusted in accordance with the status of each individual athlete.

Additional factors affecting external match load

From the previous section it is apparent that research has shown that residual fatigue does not have a significant effect on the external match load in the subsequent fixture for professional athletes. However, the effects of acute fatigue were found to impact the external load of individuals in periods of the game. As well as fatigue, other factors affecting external match load have been investigated in order to gain a more comprehensive insight into what causes differences in external match load between individuals. Factors such as playing positions, quality of opposition, location of fixture (home vs away), match status and playing style have all been found to have an effect on external match load (Lago et al., 2010; Lago & Martin, 2007; Taylor et al., 2008) and have been discussed at greater detail in earlier sections of this literature review. An additional factor which has been found to affect the external match load is the level of the footballer (Mohr et al., 2003). Mohr et al., (2003) found that elite domestic players performed 28% more high intensity running (2.43 vs 1.90 km; $P < 0.05$) and 58% more sprinting (650 vs 410 m; $P < 0.05$) than professional players of a lower standard. This research suggests that the better the standard of player, the more high-intensity activity performed throughout the match. As discussed previously, high-intensity periods of the game are often decisive to the outcome (Wragg et al., 2000), therefore it is logical to predict that the better players are the ones who can perform a greater amount of high-intensity activity.

Interestingly, a recent study by Bradley et al., (2010) found no significant difference ($P>0.05$) in high-intensity running between elite level domestic players and international players (2,520 ± 678 vs. 2,745 ± 332 m). This is in contrast to the findings of Mohr et al., (2003), suggesting that perhaps it is not as simple as the better quality players travel a greater distance at high intensity. Bradley et al., (2010) also, unlike Mohr et al., (2003) investigated the acceleration profiles of elite soccer players, however found no significant differences across the playing levels in the acceleration profiles. A critique of the study of Mohr et al., (2003) is that it doesn’t explore the differences in acceleration profiles between the different playing levels, as accelerations and decelerations have been found to be key determinants of external match load (Rago et al., 2020).

The majority of the research that exists examining comparisons of external match load between playing standards is focused on the international level, the elite domestic level and the moderate professional level (Mohr et al., 2003; Bradley et al., 2010). A level of standard that has little research devoted to it is the non-league/semi-professional level. Within football league systems the majority of the clubs are classified as semi-professional, in most countries typically only the top league is professional. In England however, the top four leagues are professional (92 teams), whereas the semi-professional level is comprised of 296 teams. Due to the sheer volume of teams and their associated players, it is logical to suggest that more research needs to be compiled at this level to obtain more of an understanding of the physical demands placed upon these athletes.

Several pieces of literature have examined lower standard and amateur players (Saltin, 1973; Ohashi et al., 1988; Van Gool et al., 1988), however many of these studies are now dated.

There has been a sizeable change in the playing standard and professionalism of non-league/semi-professional football over the last 30 years, with the majority of clubs in the top division of non-league (National League) now being full-time (professional). Moreover, it is also now common practice for semi-professional teams to use MEMS devices to monitor and condition their players (Swallow et al., 2020), therefore the aforementioned studies (Saltin, 1973; Ohashi et al., 1988; Van Gool et al., 1988) are likely to no longer be representative of the current non-league/semi-professional level of football.

Recent advancements in the accessibility and affordability of MEMS have resulted in an increase in use across the lower levels of the English football pyramid (Swallow et al., 2020). Research by Thorpe & Sunderland (2012) found that semi-professional players run on average 9,742 ± 1,025 m per 90 minutes and spent 6 ± 2% of the game at high intensity. These values indicate that non-league players cover a lesser total and high-speed distance than professional athletes, which has been suggested to be attributed to the differences in technical demands required in the lower leagues (Bradley et al., 2013). The research by Thorpe & Sunderland (2012) however was collected from a team in the National League (fifth division), which is the top division of non-league. This data is not representative of the non-league as a whole as it is only the data from one club who are in the top division; therefore more data is needed to be collected across the non-league/semi-professional levels in order to get a more comprehensive idea of the external match load performed in non-league.

The study by Thorpe & Sunderland (2012) also does not provide a comparison between semi-professional and professional footballers. Many factors have been found to influence external match load (quality of opposition, location of fixture home vs away, match status and playing style), therefore an activity profile from multiple matches should be obtained to account for the effect that these factors have on a single game. From reviewing the literature, there are no studies to date which aim to compare the external match load of semi-professional football players to professional football players. It is important to compare the external load experienced at different levels of football to get a greater understanding of the physical demands required at each level. This will allow coaches and players alike to evaluate the physical status of their team/themselves in comparison to teams/players at different levels of playing standard, and develop training programmes to maximise performance levels and perhaps facilitate a transition through the different playing levels as a result.

Players such as Jamie Vardy, Chris Smalling and Michail Antonio have all shown that the transition from the semi-professional level to the top of the professional game is possible, with many other players joining them in the progression from semi-professional to professional football. This research study could hopefully demonstrate to those playing semi-professional football the differences in physical demands required to play at the professional level, which may in turn encourage these players to reach the physical levels of those playing professional football and perhaps enable a transition through the English football pyramid like the players previously mentioned.

Summary and hypotheses

In summary, research has found multiple factors to have an effect on the external match load of footballers. Playing position, quality of opposition, location of fixture home vs away, match status and playing style have all been found to influence external match load (Lago et al., 2010; Lago & Martin, 2007; Taylor et al., 2008). The quality of player has also been found to have an effect on external match load (Mohr et al., 2003; Thorpe & Sunderland, 2012), with better quality players (players playing at a higher playing standard) travelling a greater distance at high-speed than their lesser quality counterparts. However, these studies only compared high-speed running between different quality of players. Both accelerations and decelerations have a significant effect on the external load experienced in match-play (Dalen et al., 2016), and therefore need to be investigated when comparing external match load between players at different playing standards.

There is a paucity of research that has examined match load/training load of semi-professional football players. Moreover, no studies to the author's knowledge currently exist comparing the external match load experienced by semi-professional footballers to professional footballers. The only comparisons between playing levels exist at the elite-domestic standard and international standard (Mohr et al., 2003; Bradley et al., 2010). Therefore, an aim of this thesis is to quantify the external match load faced by semi-professional footballers and compare this to professional levels of the English football pyramid. The specific experimental hypothesis is:

$H1_1$) The external match load experienced by players will significantly increase with levels of the football pyramid.

$H1_0$) The external match load experienced by players will be no different between different levels of the football pyramid.

As well as this being the main aim of this thesis, a secondary aim is to examine and compare the effect that a congested fixture schedule has on the external match load of non-elite professional and semi-professional football players. A wealth of research exists examining the effects that a congested schedule has on elite professional players (Carling et al., 2012; Dellal et al., 2015; Dupont et al., 2010), with the findings of these studies being consistently dictating that a congested fixture schedule has no effect on external match load. The findings of these studies drive the second experimental hypothesis of this thesis:

$H2_1$) Periods of fixture congestion will have no effect on the external match load of the athletes.

$H2_0$) Periods of fixture congestion will have an effect on the external match load of the athletes.

However, these studies are not representative of non-elite professional and semi-professional football players. These football players experience similar fixture schedules where they are required to play multiple games a week, however the facilities and strength of squads are weaker than those at the elite level. Therefore, research ought to be carried out at these levels to explore whether a congested fixture schedule has an effect on the external match load levels of these players. With this being said, the third specific experimental hypothesis is;

$H3_1$) A congested fixture schedule will have a significantly greater effect on the external match load as the level of football decreases.

$H3_0$) The level of football will have no effect on whether a congested fixture schedule effects external match load.

The fourth and final aim of this thesis is to examine and compare whether certain points in the season (e.g. early season, Christmas period, end of season) can have an effect on external match load in times of fixture congestion at the non-elite professional and semi-professional level. This study was investigated due to a lack of research on whether different stages in the season has an effect on the physical performance of players (Mohr et al., 2003). When reviewing the literature that examines whether a congested fixture schedule has an impact on the external match load of football players (Carling et al., 2012; Dellal et al., 2015; Dupont et al., 2010), none of the research looked at whether different points in the season has an effect on the physical performance of the players. In England, one of the most popular discussions is the effect of the congested Christmas period on the external match load of the players (Odetoyinbo et al., 2008), however, to the author's knowledge, no research has explored whether the specific point in the season has an effect on the physical performance of the players. The specific experimental hypothesis for this aim is:

$H4_1$) The point in the season will significantly impact the external match load in times of fixture congestion to a greater extent as the level of football decreases.

$H4_o$) The level of football will have no effect on whether the point in the season has an effect on external match load in times of fixture congestion.

Methods

Participants

This study consisted of 51 outfield football players (18 defenders, 20 midfielders, 13 attackers) competing at both the professional (21 participants; 7 DEF, 9 MID, 5 ATT) and semi-professional level (30 participants; 11 DEF, 11 MID, 8 ATT) of football in England. The professional players were employed by a club in League 1 (Third level of English football pyramid), whereas the semi-professional athletes were employed by a club in the Isthmian League South East Division (Eighth level of English football pyramid). Goalkeepers were excluded from data analysis due to the differential nature of their playing demands. This study received ethical approval from The School of Sport and Exercise Sciences Research Ethics and Advisory Group (REAG) at the University of Kent (ethics reference number: 12_20_21).

Study design and procedure

The design of this study was observational in nature in order to quantify and compare the external match load of the professional and semi-professional football players over the course of the 2019/2020 annual season, which took place from August 2019 – March 2020 before the season was abandoned due to COVID-19. Both teams competed in four official competitions throughout the season, with the professional players competing in the League Cup, FA cup, Checkatrade Trophy and League One, whereas the semi-professional players competed in the FA cup, FA Trophy, Kent County Cup and the Isthmian League. Both teams also completed pre-season friendly games before their competitive seasons commenced, however this data was not considered for analysis due to the non-competitive nature of pre-season friendlies.

Measures of external match load were collected via MEMS devices from 58 games across the 2019/2020 season (43 professional games, 15 semi-professional games). These measures being total distance, high speed distance, accelerations, decelerations and player load. The two football teams used different MEMS devices, with the professional club using the GPSports™ 15 Hz device (SPI HPU, GPSports™, 15 Hz, Canberra, Australia) and the semi-professional club using the PlayerTek™ 10 Hz device (Catapult Sports, 10 Hz, Melbourne, Australia). These devices provide position, velocity and distance. Both devices are also equipped with a 100 Hz tri-axial accelerometer which measures movement in three planes (longitudinal, anterior-posterior and mediolateral), the sum of which is used to calculate a composite vector magnitude, which is expressed as G-force.

Each player wore the device between the scapula and the device was secured using a custom-fitted vest supplied by the manufacturer. All data was handled in accordance with recommendations from research by Malone et al., (2017) and the data was downloaded after each game via the company's respective software (GPSports™ Cloud, Canberra, Australia; PlayerTek™ Cloud, Catapult Sports Group, Australia). The data was collected by the Sports Science department of each football club, with both clubs providing permission for the use of their anonymised data within this thesis.

Once this raw data was obtained from both clubs, the data was checked and cleaned for errors or missing data, with files selected for analysis in accordance with the inclusion and exclusion criteria:

Inclusion criteria:

- Data must have been recorded within competitive matches.
- Data must represent at least 50% of the total playing time of the match (i.e. the player played at least 45 minutes of the match)
- Players must complete at least 5 km in distance in the game for the Data to be included
- Data from players competing in at least 1/3 of the season

Exclusion criteria:

- Data recorded in non-competitive matches
- Data that has missing periods in games (periods where the MEMS device hasn't picked up any data)
- Data from players that played less than 50% of a game.
- Data from players who did not complete 5 km in distance in the game
- Data from players completing less than a third of the season

Consequently, 31 players had sufficient data to qualify for analysis, 17 professionals (6 DEF, 6 MID, 5 ATT) and 14 semi-professionals (5 DEF, 6 MID, 3 ATT). Five games worth of data was picked at random for each player using a process of random number selection. The reason only five games of data was used for analysis was because the data set given to me by the semi-professional club was rather incomplete, with only fifteen games of data included in the data set and as well as this in semi-professional football there is a large player turnover, due to regulations around player contracts and the easy registration of these players. Therefore, to get a sufficient amount of players with enough quality data for analysis, five random games worth of data was decided upon as 14 semi-professional players had at least five games of complete data. So that the amount of games used for analysis would not be a confounding variable, five random games worth of data from the professional players throughout the 2019/2020 season was also used for analysis.

To assess the impact of fixture congestion on match load, additional selection criteria was introduced for data to be included within the study. This was that data must have been collected in a week where three fixtures took place. Data from 22 players was subsequently used for analysis (11 professional players; 5 DEF, 2 MID, 4 ATT and 11 semi-professional players; 3 DEF, 6 MID, 2 ATT). The periods of time in which these fixtures occurred were September, December and the first week of January as this was the only time in the season where both clubs had a congested fixture schedule. Therefore, this time period was used for both data sets to avoid the time in the season being a confounding variable within the analysis. This analysis also therefore enabled investigation as to whether the time of season (e.g. early season, Christmas period, end of season) influences external match load measures between professional and semi-professional players.

Dependent Variables:

Total distance

Total distance was measured in kilometres (km) and provides a global representation of the volume of exercise (walking, jogging, sprinting) and is a simple way to assess an individual player's contribution to a team performance.

High speed distance

High speed distance (HSD) was measured in meters and was classified as distance travelled above the speed of 5 $m.s^{-1}$ according to both Playertek™ and GPSports™ default speed zones.

Accelerations

Accelerations are the number of times (counts) that a player's acceleration was greater than the acceleration threshold for at least 1 second. The acceleration threshold for the professional club's data was 2.5 $m.s.s^{-1}$, whereas the threshold for the semi-professional club's data was 3 $m.s.s^{-1}$. The difference in acceleration thresholds was due to the two teams using different collection software, which could not be adjusted due to the retrospective nature of the analysis. Due to the differences in the classification of an acceleration and deceleration between the two collection software's, I came to the conclusion that no comparison could be made between the two playing levels in terms of the amount of accelerations and decelerations made per 90 minutes. However a comparison could still be made within teams, which was useful to examine the second aim of this study - to assess the impact of fixture congestion on match load

Decelerations

Decelerations are the number of times (counts) that a player's deceleration is greater than the deceleration threshold for at least 1 second. The deceleration thresholds for both clubs were the same as the acceleration thresholds outlined above. Due to the differences in the classification of an acceleration and deceleration between the two collection software's, I came to the conclusion that no comparison could be made between the two playing levels in terms of the amount of accelerations and decelerations made per 90 minutes. However a comparison could still be made within teams, which was useful to examine the second aim of this study - to assess the impact of fixture congestion on match load.

Player load

The Playerload™ metric uses accelerometer data to calculate the total load or activity level in arbitrary units that the player has undergone throughout the match. Research has shown that Playerload™ is a valid and reliable measure and can provide important insights into player activity (Barrett et al., 2014). Playerload™ itself is synonymous with Playertek™, therefore Playerload™ is only calculated for teams using Playertek™ devices. GPSports™, on the other hand, uses 'body load™' in order to calculate the load and activity level faced by athletes when wearing their devices. Both calculations are based on the root mean square of the squared instantaneous rate of change in acceleration in each of the three vectors (X, Y and Z axis) and divided by 100. Each calculation is based on the manufacturer and is specific to the type of accelerometer used (Boyd et al. 2011; Gomez-Piriz et al. 2011).

The professional club's data uses body load™ to calculate the load and activity level faced by athletes, on the contrary the semi-professional club's data uses Playerload™. As both of the calculations are different, in order to standardise both data sets, so that a comparison could be made between the player load values from both clubs player load values for each game were calculated as a percentage of the maximum player load output recorded in the season. For example, if a player had a maximum player load bout of 400 (AU) in the season and if - in one of the five randomly selected matches - their player load value was 300 (AU), the player load value used for analysis would be 75%. This method of standardising player load was used for a comparison between both clubs and also when analysing whether periods of fixture congestion affected match load at different points in the season.

Statistical analysis:

All statistical analyses were conducted using IBM SPSS Statistics 26. After checking relevant parametric assumptions, a univariate ANOVA was used to assess differences in external match load measures of total distance, high-speed distance, accelerations, decelerations, and player load with player performance level and the game number as fixed factors. If assumptions of sphericity were violated, then the Greenhouse-Geisser correction was used to determine if the results were significant.

A two-way repeated measures ANOVA was used to examine if significant differences existed in dependent variables across player performance level (2 levels) and time of the season (3 levels) during periods of time when teams experienced fixture congestion.

Unless shown otherwise, data is displayed as mean ± standard deviation.

Results

Match Load from 5 randomly selected games during the season

Statistical analysis revealed no significant interaction between team x game for total distance covered (P=0.833). A main effect was however found for team (P<0.001), with the average total distance per game being significantly greater for the professional players than the semi-professional players (10.93 ± 2.46 vs 9.02 ± 1.56 km for professional vs semi-professional players respectively; P<0.001; see Figure 3). In contrast, no significant main effect of game (P=0.915).

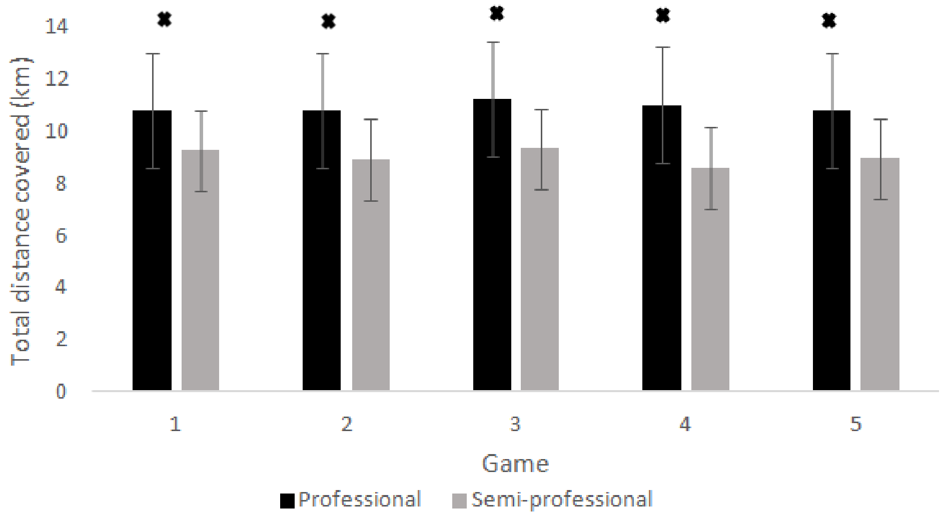


Figure 3: Comparison of total distance covered between the professional players and the semi-professional players in each of the five randomised games.✖ = significantly greater than the semi-professional players.

No significant interaction was found for high-speed distance between team x game (P=0.597; see Figure 4). There was no main effect of team (P>0.05), so average high-speed distance as not significantly different between teams (928.3 ± 280.8 vs 947.8 ± 339.4 m for professional and semi-professional players respectively; P=0.70). In addition, no significant main effect was found for game (P=0.926).

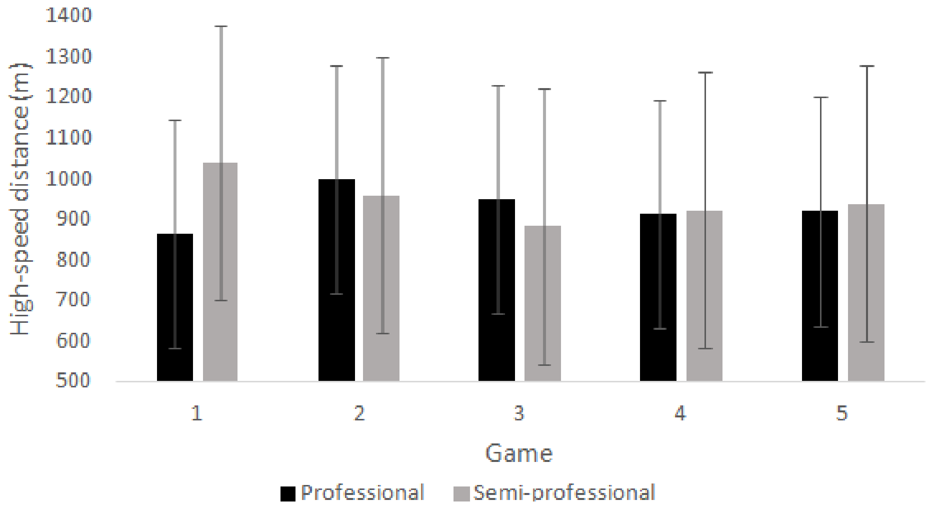


Figure 4: *Comparison of high-speed distance (distance covered at a speed >5 m.s^{-1}) covered between the professional players and the semi-professional players in each of the five randomised games.*

No significant interaction was found for player load between team x game (P=0.548). A significant main effect was however found for team (P<0.001), with the average player load recorded per game being significantly greater for the semi-professional players than the professional players (68.8 ± 18.9% vs 88.6 ± 12.2 for professional vs semi-professional respectively; P<0.001; see Figure 7). No significant main effect was found for game (P=0.991).

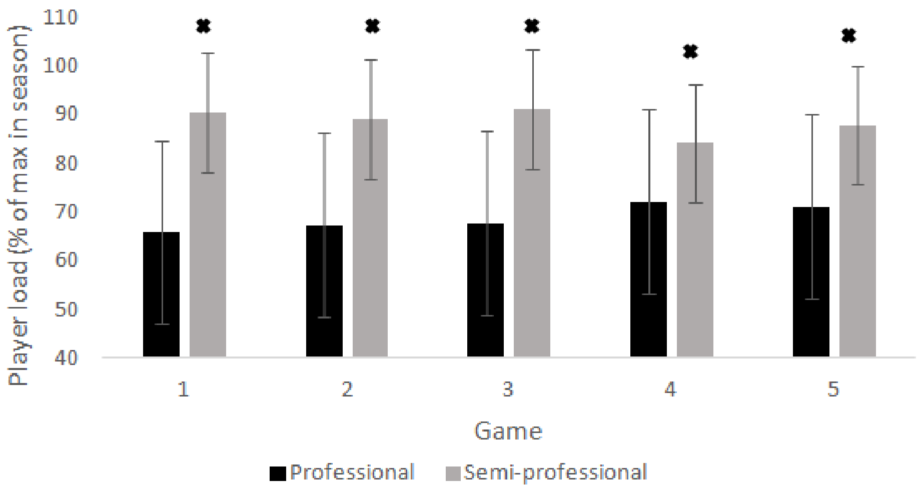
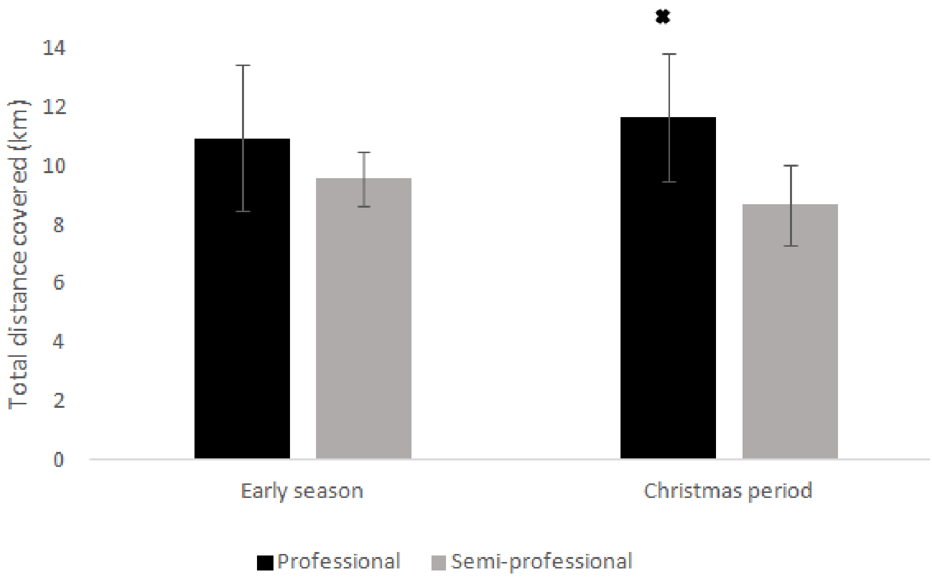


Figure 5: *Comparison of player load (as a % of the maximum player load value recorded in a match during the 2019/2020 season) between the professional players and the semi-*

professional players in each of the five randomised games.✖ = significantly greater than the professional players.

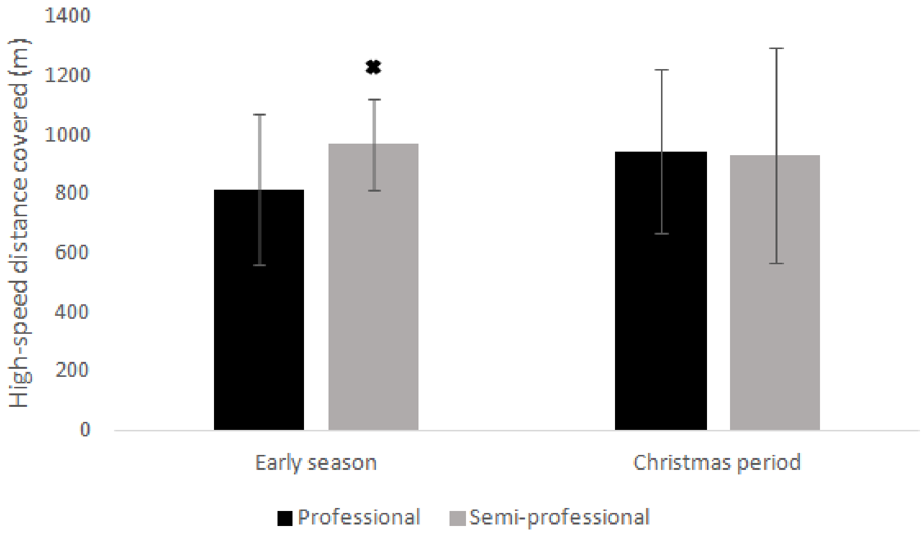
<u>*Match Load during periods of fixture congestion*</u>

No significant main effect was observed between total distance x point in season (early season vs Christmas period) x game (1, 2 or 3) x team (professional vs semi-professional) (P=0.404) in congested periods of the season. There was also no significant interaction for total distance covered between team x game in the early part of the season, or at Christmas time (P=0.764 and P=0.397, respectively). As well as this, no significant effect was found between total distance x time in season x team (P=0.205). There was no significant difference in total distance between teams at the start of the season (P=0.135), however at Christmas time a significant difference was evident (P=0.004; see Figure 8), with professional players covering a significantly greater average distance per game than semi-professional players (11.68 ± 2.17 km vs 8.69 ± 1.37 km). There was no main effect of game (P=0.887), as well as no significant interaction between total distance x time in season (P=0.900).



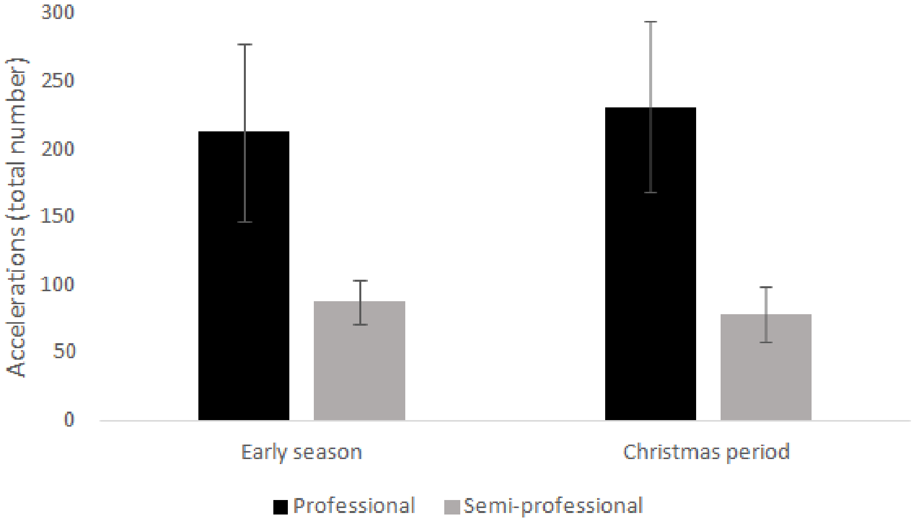
<u>*Figure 6:*</u> *Comparison of total distance covered (km) per 90 minutes between the professional players and the semi-professional players in periods of congested fixtures at the start of the season (early season) and at the mid-point of the season (Christmas period). ✖ = significantly greater than the semi-professional players.*

No significant main effect was observed between high-speed distance x point in season x game x team (P=0.304) during congested parts of the season. No significant interaction was observed, either, for high-speed distance between team x game in the early part of the season, or at Christmas time (P=0.284 and P=0.515, respectively). Similarly, no significant effect was observed between high-speed distance x time in season x team (P=0.347). At the start of the season semi-professional players covered significantly more distance at high speeds than professional players (815.2 ± 253.3 m vs. 968 ± 155.8 m for professional vs semi-professional players respectively; P=0.031; see Figure 9). No significant main effect was found for team during the Christmas period (P=0.931). No significant main effect was found for game (P=0.823), or high-speed distance x time in the season (P=0.606).



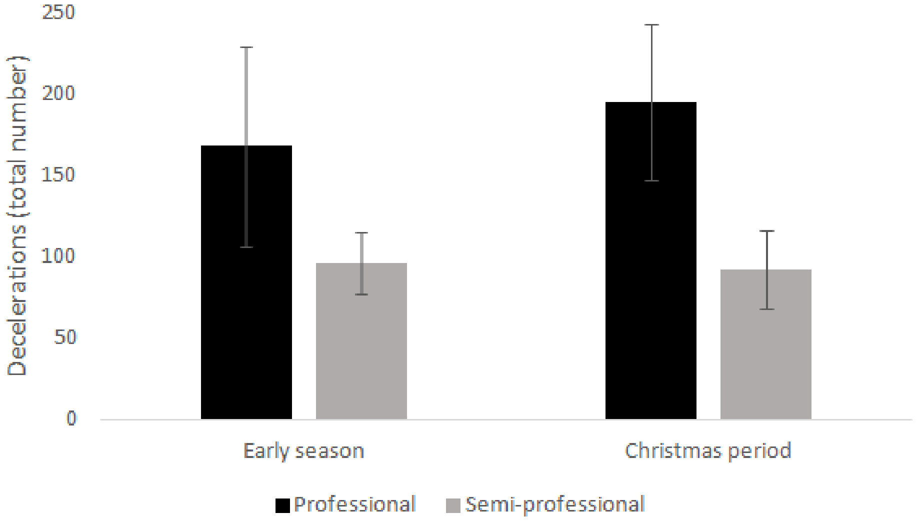
<u>Figure 7:</u> Comparison of high-speed distance covered (m) per 90 minutes between the professional players and the semi-professional players in periods of congested fixtures at the start of the season (early season) and at the mid-point of the season (Christmas period). ✖ = *significantly greater than the professional players.*

No significant main effect was observed between accelerations x point in season x game (P=0.977) in congested periods of the season. No significant main effect was found for accelerations x game (P=0.911), as well as no significant main effect of accelerations x time in season (P=0.785).



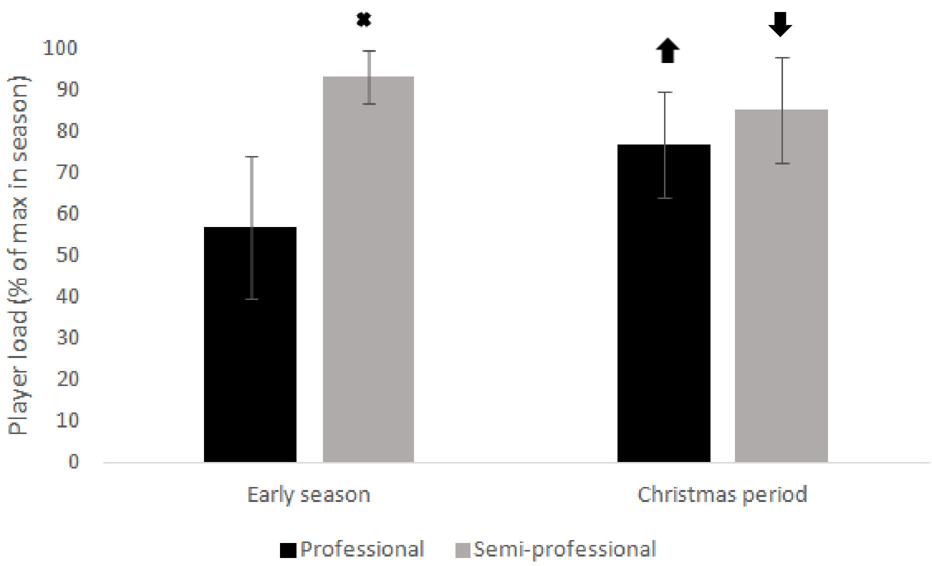
<u>Figure 8:</u> Comparison of the number of accelerations per 90 minutes seen in the professional players and the semi-professional players in periods of congested fixtures at the start of the season (early season) and at the mid-point of the season (Christmas period).

No significant main effect was observed between decelerations x point in season x game (P=0.674) during congested periods in the season. No significant main effect was found for decelerations x game (P=0.867), in the same way no significant main effect was found for decelerations x point in season (P=0.403).



<u>Figure 9:</u> Comparison of the number of decelerations per 90 minutes seen in the professional players and the semi-professional players in periods of congested fixtures at the start of the season (early season) and at the mid-point of the season (Christmas period).

No significant main effect was observed between player load x point in season x game x team (P=0.372) in congested periods of the season. Likewise, no significant interaction was observed for player load between team x game during congested periods in the early part of the season or at Christmas time (P=0.611 and P=0.359, respectively). significant interaction was nevertheless found between player load x point in season x team (P=0.002), with semi-professional players going from a player load value (as a % of the maximum player load value recorded throughout the season) in the early season of 93.24 ± 6.44 % to 85.27 ± 12.69 % in the Christmas period, whereas professional players experienced an increase in their player load values from 56.81 ± 17.25 % in the early part of the season to 77.01 ± 12.8 % at the Christmas period. During the congested period at the start of the season semi-professional players recorded greater player load values (as a % of the maximum player load value recorded throughout the season) than the professional players (93.24 ± 6.44 vs 56.81 ± 17.2 %, P<0.001; see Figure 12). Although no significant main effect was found for team during the congested Christmas period (P=0.136). There was no significant main effect for player load x game (P=0.941) and there was also no significant main effect for player load x point in season (P=0.147).



<u>Figure 10:</u> Comparison of player load (as a % of the maximum player load value recorded in a match during the 2019/2020 season) per 90 minutes between the professional players and the semi-professional players in periods of congested fixtures at the start of the season (early season) and at the mid-point of the season (Christmas period).✖ = significantly greater than the professional players.🡅 = significant increase from the early part of the season.🡇 = significant decrease from the early part of the season.

Discussion

Comparison of external match load between playing levels

The main aim of this thesis was to examine and compare the external match load experienced by professional and semi-professional football players. The results of this study suggest that there are significant differences in match load between professional and semi-professional players, with 2 out of the 3 external match load metrics being significantly different between the two different playing levels. Specifically, total distance covered (10.93 ± 2.46 vs 9.02 ± 1.56 km for professional vs semi-professional players respectively; P<0.001) was significantly greater for the professional football players than the semi-professional footballers (as shown in figures 3). In contrast, player load values (calculated as a % of the max player load value in the season) were significantly greater for the semi-professional footballers as opposed to the professional players (68.8 ± 18.9% vs 88.6 ± 12.2 for professional vs semi-professional players respectively; P<0.001). However, there were no significant differences between the playing levels when comparing high-speed distance covered per game (928.3 ± 280.8 vs 947.8 ± 339.4 m for professional and semi-professional players respectively; P=0.70).

Is external match load different between Professional and Semi-professional football players?

The most popular measure used to quantify external match load, as suggested by a recent review of the literature, is high-speed running distance (Rago et al., 2020). When applying this to the current results, it is not possible to accept the first hypothesis ($H1_1$; The external match load experienced by players will significantly increase with levels of the football pyramid), as, whilst the professional players travelled a significantly greater total distance per 90 minutes than the semi-professional players, there was no significant difference between the playing standards when comparing the amount of high-speed distance covered by the respective football players.

Player load is used to quantify external match load in team sport players (Barrett et al., 2014). Due to differences in how this is calculated from GPS and accelerometer data by equipment manufacturers, it is difficult to directly compare across studies which have used different systems. Barrett et al., (2014) did however find ‘Playerload™’ (player load calculation synonymous to Playertek™ MEMS devices) to have moderate to high test-retest reliability and found that it is able to effectively monitor external load during intermittent and multidirectional running (Barrett et al., 2014). When comparing the load values experienced between the two different playing levels in the current study, the semi-professional football players were found to elicit significantly greater player load values than the professional football players. Therefore, relating these results back to the hypotheses, it is again not possible to accept the first experimental hypothesis.

Interestingly, when data on distance covered are considered alongside player load data, results suggest that even though professional players cover a significantly greater distance, it does not mean that their external match load is significantly greater than the semi-professionals. Total distance covered is a measure of exercise volume and is usually dependent on the exercise duration; it is also used as a measure of exercise intensity when it is scaled to the duration of exercise (Clemente et al., 2019b; Malone et al., 2014; Owen et al., 2017). However, total distance may not provide an accurate measure of external match load as it does not account for the intermittent activities in football match play. For example, players perform from 150 to 250 brief intense actions throughout the course of the 90 minutes (Mohr et al., 2003), approximately changing their direction of movement 1,100 times (Andrzejewski et al., 2015). These actions involve accelerations, decelerations as well as running at high speed, which all contribute the external match load faced by an athlete. Therefore, the total distance covered by an athlete does not provide a complete measure of the external match load experienced in a game, meaning that, despite the professional football players covering significantly more ground than the semi-professional footballers, it is not possible to conclude that they have a higher overall external match load.

Do periods of fixture congestion effect match load, and does playing level matter?

A second aim of this thesis was to examine whether the periods in the season where teams have a congested fixture schedule affect the external match load of athletes.

The results of this study suggest that periods of fixture congestion have no effect on the external match load in subsequent games. All five of the external match load measures were not significantly affected by periods of congested fixtures. The total distance covered was not significantly affected when three games were played in the space of seven days (10.37 ± 2.09 vs 10.33 ± 2.34 vs 10.59 ± 2.46 km, respectively; P=0.877). High-speed distance covered was also not significantly affected by fixture congestion (901.4 ± 329.9 vs 890.9 ± 271.8 vs 917.2 ± 242.8 m, respectively; P=0.823). Similarly, the number of accelerations per game were not affected by a congested fixture schedule (165.2 ± 83.2 vs 167.5 ± 90.6 vs 168.9 ± 85.6, respectively; P=0.911), as well as the number of decelerations per game (143.6 ± 61.4 vs 146.8 ± 63.1 vs 150.8 ± 66.4, respectively; P=0.867). Furthermore, the player load values were not affected by a congested fixture schedule (74.6 ± 19.4 vs 74.4 ± 19.6 vs 75.9 ± 19.1 %, respectively; P=0.941). Therefore, the results of this study mean that it is possible to accept the second experimental hypothesis that periods of fixture congestion will have no effect on the external match load of the athletes. In addition to this, the findings of this study also support those of other research studies, which have found that no significant differences in physical and technical performance occur from match to match in times of fixture congestion (Carling et al., 2012; Dellal et al., 2015; Dupont et al., 2010).

The majority of research examining the effects of fixture congestion on external match load involved elite-professional football players (Carling et al., 2012; Dellal et al., 2015; Dupont et al., 2010), meaning the results of these studies cannot be generalised to all standards of football. No studies to the author's knowledge had compared the effect of fixture congestion on match load between different playing levels. However, due to the recovery facilities and the depth of squads improving as the playing level increases, it is likely that a congested fixture schedule will have a significantly greater effect on the external match load at lower levels playing levels. However, the results of this study suggest that playing level does not influence external match load during periods of fixture congestion. Therefore, despite there being no previous research – to the author's knowledge – comparing the effect of fixture congestion on match load between different playing levels, the results of this study are able to generalise the findings of the research by Carling et al., (2012), Dellal et al., (2015) and Dupont et al., (2010) to the non-elite professional and semi-professional playing standard of football. Furthermore, the results of this study mean that it is not possible to accept the third experimental hypothesis that a congested fixture schedule will have a significantly greater effect on the external match load as the level of football decreases.

Does the point in the season have an effect on whether fixture congestion effects match load at different playing levels

Another research question this thesis aimed to investigate was whether the point in the season had an effect on external match load at different playing levels during periods of fixture congestion. Similarly to the previous investigation, no prior research – to the author's knowledge – had been made into whether the point in the season has an effect on external match load at any playing level. For this reason, the fourth experimental hypothesis was that $H4_1$) The point in the season will significantly impact the external match load in times of fixture congestion to a greater extent as the level of football decreases.

The results of this study show that the point in the season does not have an effect on match load at different playing levels in times of fixture congestion. As seen in the results section (displayed as 'team x time in season x game'), total distance (P=0.404), high-speed distance (P=0.304), and player load (P=0.372) were all found to experience no significant interaction between the point in the season and the playing level in periods of congested fixtures. The point in the season also had no effect on any of the external load measures, regardless of the playing level and whether the fixtures were congested (as shown in the results section as 'main effect of time in season'). Therefore, the results of this study suggest that it is not possible to accept the fourth experimental hypothesis ($H4_1$; The point in the season will significantly impact the external match load in times of fixture congestion to a greater extent as the level of football decreases), as the point in the season was not found to significantly affect any of the external match load variables.

Interestingly however, the results found that player load was significantly affected by point in the season at different playing levels (P=0.002), with semi-professional players going from an average player load value (as a % of the maximum player load value recorded throughout the season) in the early season of 93.24 ± 6.44 % to 85.27 ± 12.69 % in the Christmas period, whereas professional players experienced an increase in their player load values from 56.81 ± 17.25 % in the early part of the season to 77.01 ± 12.8 % at the Christmas period. Player load was the only measure significantly affected by the point in the season at different playing levels, therefore this does not mean it is possible to accept the fourth experimental hypothesis. However, these findings could guide future research studies to investigate whether player load is significantly affected by the point in the season at different playing standards of football, or whether these results were an anomaly.

Study Limitations

Unfortunately, due to COVID-19, primary data collection was not possible in this study due to the semi-professional club's 2020-2021 season being abandoned in November. For this reason, it was necessary to conduct a study based upon secondary data sets, and therefore, both data sets had various issues related to missing data. As a consequence, procedures were put in place to facilitate comparability between the quantities of data within the two datasets (see methods section). The main limitation with the two different data sets is that the two clubs use different MEMS technology systems, with the professional club using the GPSports™ SPI HPU system and the semi-professional club using the Playertek™ system.

The two MEMS devices are also different in the resolution of data acquisition, with the GPSports™ sampling at 15 Hz and the PlayerTek™ 10 Hz device. With the manufacturer and sampling rate of the devices being different for both clubs, a limitation exists as the accuracy and reliability of MEMS devices change dependent on a range of factors such as the manufacturer and sampling rate (Akenhead et al., 2014). For example, research has dictated that a sampling rate of 10 Hz has been found to be more accurate and reliable sampling rate when compared to a rate of 15 Hz (Johnston et al., 2014; Scott et al., 2016; Waldron et al, 2011).

The study conducted by Johnston et al. (2014) assessed the validity and variability of the Playertek™ 10 Hz and GPSports™ 15 Hz device (the two devices used in this study) and found that in general the 10 Hz device measured movement demands with greater validity and reliability. This research suggests that comparisons made between data collected using the two different units has its limitations due to the differences in the validity and reliability of each respective unit. This is a limitation of my study as the data sets given to us by the two different football clubs was collected using the Playertek™ 10 Hz and the GPSports™ 15 Hz devices. However, as the data was retrospective data, this limitation could not be overcome. The reader should therefore be aware that this limitation still exists in this study.

As well as this, Johnston et al. (2014) found that both devices (Playertek™ 10 Hz and GPSports™ 15 Hz) were incapable of reliably measuring distance covered at speeds greater than 20 $km.h^{-1}$ (typical error of measurement >10%). The findings of this study are supported by further research by Rampinini et al., (2015), which found good accuracy for the GPS when measuring total distance and high-speed running (CV% of 1.9 and 4.7%, respectively) but poor accuracy when measuring very high-speed running (>5.56 $m.s^{-1}$; CV% of 10.5). As evidenced in these studies, it is clear to see that MEMS devices have limitations when players are travelling at very high speeds, with accuracy and reliability diminishing at very high levels of speed.

Research by Akenhead et al., (2014) also suggests that the accuracy and reliability of MEMS devices (Catapult S4 10 Hz model) is compromised at accelerations exceeding 4 $m.s^{-1}$ (SEE=0.32 $m.s^{-1}$). This research study - coupled with the two aforementioned - has implications for my study, as the quantification of high-speed running as well as both accelerations and decelerations have an element of accuracy and reliability issues. The reader should be aware that these issues exist and may potentially have implications on the findings of my study, specifically in the quantification and comparison of high-speed running, accelerations and decelerations between and within playing levels.

Differences between data acquisition systems led to other difficulties as well, specifically when comparing the player load values of the two data sets. The GPSports™ system and the Playertek™ system use different calculations to determine the player load of the athlete, with GPSports™ using ‘body load™’ and Playertek™ using ‘Playerload™’. As both of the calculations differ, different player load values will be returned from each system. Therefore, in order to standardise both data sets and overcome this limitation, player load values for each game were calculated as a percentage of the maximum player load value recorded throughout the season.

Moreover, the GPSports™ system classifies a significant acceleration and deceleration as an acceleration or deceleration greater than 2.5 $m.s.s^{-1}$, whereas the Playertek™ system classifies a significant acceleration/deceleration as any acceleration/deceleration greater than 3 $m.s.s^{-1}$. This limitation could not be overcome as the data inherited was secondary data. As a result of this limitation not being able to be overcome, it was not possible to compare the differences in accelerations and decelerations per 90 minutes between professional and semi-professional football players. Whilst it was not possible to compare accelerations and decelerations between playing levels, it was possible to compare within the playing levels, which was useful to examine the second aim of this study - to assess the impact of fixture congestion on match load.

To overcome this limitation in future research, the MEMS devices used by the different clubs should be obtained from the same manufacturer and use the same sampling rate. Ideally, if the football clubs had unlimited resources, a semi-automated video tracking system would be used instead of MEMS devices. A literature review conducted by Sparks et al., (2017) found that a semi-automated tracking system for monitoring external load is the most popular in literature (18 out of 27), with advantages over MEMS units in the accuracy and reliability of measurements. However, due to the price of these systems in comparison to MEMS devices and the financial constraints that clubs in the lower leagues face, it is not realistic to suggest that future research dedicated to quantifying and comparing the external load of professional and semi-professional footballers should use semi-automated video tracking systems.

Future directions

Further research is needed to quantify the external load encountered by players at the lower playing levels of semi-professional football. To the author’s knowledge no other studies have previously compared the external match load faced by professional and semi-professional football players. Within the English football league system, the majority of the clubs are classified as semi-professional comprising 296 teams, with the top four professional leagues comprising only 92 teams. Therefore, due to the volume of teams and players performing at the semi-professional level, it is very important to gain a greater understanding of the physical demands placed upon these athletes.

It is necessary to compare the external match load at different levels of football in order to gain a greater understanding of the physical demands needed at each playing level. This will allow both coaches and players to evaluate the physical status of their team/themselves in comparison to teams/players at different levels of playing standard and develop training programs to maximise performance levels and perhaps facilitate a transition through the different playing levels as a result.

Whilst there should be future research dedicated to quantifying and comparing the external match load at the professional and semi-professional level, it is also important to know that external match load should be looked at on an individual basis. Different factors such as playing position and playing style have been found to effect external load (Bangsbo et al., 2006; Mohr et al., 2003; Reilly & Thomas, 1976), therefore these factors should be accounted for when quantifying the external load of football players at different levels.

It is important to acknowledge that there has been caution raised against relying solely on external load to monitor the activity status of athletes (Impellizzeri et al., 2019). It is difficult to make accurate interindividual comparisons when using external load as a measuring tool for activity status, as it does not consider the internal response of the athlete to the given external load (Impellizzeri et al., 2019). This is a concern because research has found that athletes respond to the same amount of external load in different ways (Bouchard & Rankinen, 2001), for example there are low responders and high responders. A low responder is an athlete who has a lower internal response to the same external load (Impellizzeri et al., 2019). The internal response to training and match play can be influenced by many factors, such as current training status, age, nutritional status, previous training experience and genetic factors (Bouchard & Rankinen, 2001). For this reason, research such as that of Impellizzeri et al., (2019), has suggested that coupling external load and internal load measures is the most advantageous way of monitoring an athlete’s physical status. Therefore, the results of this study along with the potential findings of future studies investigating the external match load experienced at the professional and semi-professional level, should be tapered by clubs and athletes when applying the results to themselves dependent on their players/own internal response to exercise.

Conclusions

In conclusion, this study found that there were significant differences between playing levels when comparing different external load metrics, with the total distance covered being significantly greater at the professional level and player load being greater at the semi-professional level. No significant differences were found between the levels when comparing high-speed distance, which provided further support to the previous finding that neither playing level was found to exhibit a superior level of external match load.

The other noteworthy finding of this thesis was that fixture congestion did not affect match load. This finding supports previous research (Carling et al., 2012; Dellal et al., 2015; Dupont et al., 2010), and was consistent regardless of the playing level or the point in the season. The results of this study mean that the findings of Carling et al., (2012), Dellal et al., (2015) and Dupont et al., (2010) can be generalised to non-elite professional football players as well as semi-professional football players.

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