## THE UNIVERSITY OF HULL

## Quantifying Technical Actions in Professional Soccer Using Foot-Mounted Inertial Measurement Units

being a Thesis submitted for the degree of Master of Science (by Research)

in the University of Hull Faculty of Health Sciences Department of Sport, Health and Exercise Science

by

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## **Declaration**

I declare that this thesis was composed solely by myself, that the work contained herein is my own except where explicitly stated by reference or acknowledgement in the text, and that this work has not been submitted elsewhere, in whole or in part, for any other degree or processional qualification except as specified.

## List of Abbreviations, Acronyms and Symbols

Abbreviation, Acronym or Symbol	Meaning
cm	centimetres
cm <sup>3</sup>	centimetres cubed
cm·s <sup>-1</sup>	centimetres per second
CD	central defender
СМ	central midfielder
R <sup>2</sup>	coefficient of determination
CV	coefficient of variation
CI	confidence interval
••s <sup>-1</sup>	degrees per second
DNC	did not complete
DOM	dominant foot
EPPP	Elite Player Performance Plan
EFL	English Football League
EPL	English Premier League
$\eta^2$	eta squared
FN	false negative
FP	false positive
FIFA	Fédération Internationale de Football Association
FA	Football Association
f	frequency
$f \cdot \min^{-1}$	frequency per minute
GPS	global positioning systems

g	grams
>	greater than
HR	heart rate
Hz	Hertz
IMU	inertial measurement unit
К	kappa
kg	kilograms
km·h <sup>-1</sup>	kilometres per hour
kPa	kilopascal
<	less than
x	mean
$\overline{X}^{\mathrm{diff}}$	mean difference
m	metres
m·s <sup>-1</sup>	metres per second
MEMS	microelectromechanical systems
mm	millimetres
ms	milliseconds
min	minutes
NON-DOM	non-dominant foot
n	number
r	Pearson's product-moment correlation coefficient
·min <sup>-1</sup>	per minute
0⁄0 <sup>diff</sup>	percentage difference
0/0 <sup>inc</sup>	percentage increase

±	plus-minus
PA	proportion of agreement
Q-Q	quantile-quantile
rad∙min <sup>-1</sup>	radians per minute
®	reserved
S	seconds
Σ	sigma
SD	standard deviation
SE	standard error
SPSS	Statistical Package for the Social Sciences
ST	strikers
TN	true negative
TP	true positive
TEM	typical error of measurement
UEFA	Union of European Football Associations

## **List of Publications**

Marris, J., Barrett, S., Abt, G. & Towlson, C. (2021) Quantifying Technical Actions in Professional Soccer Using Foot-Mounted Inertial Measurement Units. *Science and Medicine in Football*, online ahead of print.

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#### Abstract

This thesis aimed to (i) establish the concurrent validity and intra-unit reliability of a foot-mounted inertial measurement unit (IMU), for measuring the frequency of technical actions performed during soccer training activities, and (ii) to quantify the within-microcycle, inter-positional, and between-drill differences in the technical actions of professional soccer training using foot-mounted IMUs.

Twelve male amateur soccer players collectively performed 8,640 ball touches and 5,760 releases, throughout a series of technical soccer tasks, repeated over two pre-determined distances. Concurrent validity was determined by calculating the proportion of agreement ( $P_A$ ) between the IMU and retrospective video analyses. Intra-unit reliability was established using the same method, supplemented by a percentage coefficient of variation (CV). Intra-operator reliability of the reference performance analyst, who conducted all analyses, was established by manually coding three randomly selected repetitions of each soccer task three times ( $P_A = 100.0\%$ ). The IMU exhibited good concurrent validity ( $P_A = 95.1\% - 100.0\%$ ) and intra-unit reliability ( $P_A = 95.9\% - 96.9\%$ , CV = 1.4% - 2.9%) for measuring ball touches and releases throughout all experimental conditions.

Twenty-one male professional soccer players' technical performance data (ball touches, releases, ball touches per minute, releases per minute), collected during training sessions throughout 24 weekly microcycles (i.e., match day [MD] minus day number [MD - n]), was subsequently analysed using general linear modelling. The most ball touches ( $\overline{X} = 218.0$ ) and releases ( $\overline{X} = 110.8$ ) were observed on MD - 1, with MD - 5 eliciting the highest frequency of ball touches per minute ( $\overline{X} = 3.8$ ) and releases per minute ( $\overline{X} = 1.7$ ). Central midfielders performed the most ball touches ( $\overline{X} = 221.9$ ), releases ( $\overline{X} = 108.3$ ), ball touches per minute ( $\overline{X} = 3.4$ ), and releases per minute ( $\overline{X} = 1.6$ ). Small-sided games evoked more ball touches per minute ( $\overline{X}^{diff} = 1.5$ ), and releases per minute ( $\overline{X}^{diff} = 0.1$ ), than previously reported in match-play. The fewest ball touches per minute ( $\overline{X} = 1.2$ ) and releases per minute ( $\overline{X} = 0.5$ ) were observed during tactical drills. The results of this thesis indicate that the foot-mounted IMU displayed promising capacity as a valid and reliable method of quantifying technical actions in soccer, as well as providing a novel understanding of the within-microcycle, inter-positional, and between-drill differences in the technical actions performed by professional players during training.

# **Chapter 1: Introduction**

#### 1.1. Background

Soccer is a popular team sport throughout Europe (Vergeer & Mulder, 2019), with the majority (n =53,077,41.2%) of global professional players (n = 128,983) playing their domestic soccer in countries regulated by the Union of European Football Associations (UEFA) (Fédération Internationale de Football Association (FIFA), 2019b). In England, the Football Association (FA) governs four professional league competitions: the English Premier League (EPL), English Football League (EFL) Championship, EFL League One and EFL League Two. Despite being responsible for majority (n = 72, 78.3%) of professional soccer clubs competing below the summit of English professional soccer, the EFL does not possess financial riches on the same scale as the prosperous EPL (Wilson et al., 2020). The average EFL Championship (£33m), EFL League One (£8m) and EFL League Two (£4m) club observed annual revenues significantly lower than the £215m achieved by their EPL counterparts in 2019 (Deloitte, 2020). Promotion to the EPL offers EFL Championship clubs a momentous financial opportunity, with a £120m reward available to those who are promoted to the top division (Wilson et al., 2018). Consequently, there exists an ever-increasing importance for prescribing professional soccer players in the EFL (and beyond) with adequate training stimuli that not only sufficiently prepares players for the multifactorial demands of competition (Morgans et al., 2014a; Nédélec et al., 2015b), but also reduces their susceptibility to injury (McCall et al., 2016b; Rossi et al., 2018) and ensures coaches have as many players available for selection as possible each week (Carling et al., 2015).

For clubs who compete in the EFL Championship, a brief pre-season preparatory period is followed by a 40-week in-season phase (Reilly, 2007), typically spanning August to May, which contains 46 domestic league and up to 13 domestic cup fixtures. This arduous competition schedule, through involvement in three domestic competitions, frequently requires players to participate in two (e.g., Saturday, Tuesday/Wednesday) and sometimes three (e.g., Saturday, Tuesday/Wednesday, Friday) fixtures within seven days (Anderson et al., 2016). Combined with winter fixture congestion (Morgans et al., 2014b), the annual competition schedule associated with EFL Championship soccer represents a significant difficulty for applied sports scientists, performance analysts, and coaches, henceforth collectively referred to as 'practitioners' (Burgess, 2017), to balance players' need to recover with the requirement to technically and tactically prepare for competition (Morgans et al., 2014a; Silva et al., 2018).

The affluence of top division professional soccer clubs has facilitated the concomitant increase in the number of multidisciplinary practitioners employed to support the players (Rothwell et al., 2020). Clubs may enlist upwards of 15 practitioners (Eisenmann, 2017), in an array of roles, to provide performance solutions to a variety of key stakeholders (Reade et al., 2009) and collectively focus upon one common goal; helping the team to secure three points on a match day (MD) (Martindale & Nash, 2013; Bartlett & Drust, 2020). As the nature of player performance has become progressively complex (Halson et al., 2019), practitioners attempt to adopt an evidence-based approach to their daily working procedures (Coutts, 2017; Fullagar et al., 2019a). Translated from the medical industry, Bartlett and Drust (2020) described evidence-based practice as the process of making informed decisions through the integration of information derived from peer-reviewed research. Accordingly, to promote knowledge transfer (Argote & Ingram, 2000), and bridge the gap between research and practice (Champ et al., 2020), it is becomingly increasingly commonplace for a researcher to be embedded within a professional club (McGuigan et al., 2018; Malone et al., 2019). Pursuant to Coutts' (2016) conceptual model, this integrated research practitioner role enables stereotypically 'fast' working practitioners to work 'slow', adopting principles of scientific rigour (i.e., robustness, quality control) to answer complex performance questions (Buchheit, 2016; 2017b; McCall et al., 2016a) and further develop the evidence base that practitioners are able to utilise (Jones et al., 2019).

Many of these questions relate to the optimisation of training activities that professional soccer players are exposed to (Bourdon et al., 2017). Traditionally, this has been achieved through the manipulation of four key components, being; the volume, intensity, duration, and type of exercise (Fry et al., 1992; White et al., 2020). The ability to objectively measure the multifactorial determinants of performance is fundamental for ensuring that training activities adequately mirror the requirements of competition (Taylor et al., 2017; Weaving et al., 2017), which subsequently increases the prospect of inducing beneficial training outcomes (Impellizzeri et al., 2005; Castellano et al., 2012). As such, practitioners are progressively seeking contemporary methods for measuring players' actions during training and match-play. One approach involves attaching wearable microtechnology to various regions on a player's body. Notable examples of 'wearables' include microelectromechanical systems (MEMS) mounted between the scapulae, that incorporate global positioning systems (GPS) and inertial measurement unit (IMU) components, frequently combined with heart rate (HR) telemetry using a chest-mounted belt, which permits the quantification of time-motion (e.g., total distance, high-speed running distance) and physiological (e.g., percentage of maximal HR) parameters.

Although practitioners have utilised MEMS for many years (O'Reilly et al., 2018), the majority (if not all) of these devices are located in the thoracic region (Barrett et al., 2014). However, the consistent evolution of wearable technology has recently contributed to manufacturers exploring the possibility of affixing devices to alternative anatomical locations (Waldron et al., 2020). Given the pivotal role that soccer players' feet play during technical performance, which is an indispensable determinant of competition success (Castellano et al., 2012; Redwood-Brown et al., 2012), the advent of a commercially available soccer-specific foot-mounted IMU appears intuitive. Implementation of such devices would broaden scholarly understanding of the periodisation strategies used to manipulate soccer players' multidimensional training load (Wallace et al., 2014; Paul et al., 2015; Scott et al., 2016a), potentially empowering practitioners to uncover otherwise hidden areas of potential performance enhancement (McParland et al., 2020). Therefore, the overall purpose of this research project, communicated by means of a written thesis, is to examine the efficacy and utility of a foot-mounted IMU for measuring the frequency of technical actions performed during professional soccer training.

# **Chapter 2: Review of Literature**

The notions of technical performance, and wearable microtechnology, are central to the aims of this research project. Therefore, the aim of the following chapter is to establish familiarity with, and critically discuss, previous research that has explored these constructs. The following review of literature (Chapter 2) is presented in six main sections. After introducing technical performance (Section 2.1.1), as one of the multifactorial demands of professional soccer (Section 2.1), several investigations that have quantified technical actions in professional soccer match-play are discussed (Section 2.2). Thereafter, the numerous methods of monitoring players' technical performance are appraised (Section 2.3), prior to examining the key components of professional soccer training (Section 2.4). Then, the prospect of using foot-mounted IMUs to quantify the frequency of technical actions performed by professional soccer players during training is explored (Section 2.5), with Section 2.6 providing an overall summary which culminates in two specific aims of this research project being established.

#### 2.1. Multifactorial Demands of Professional Soccer

Professional soccer match-play has a high-intensity intermittent nature (Bradley et al., 2010), characterised by momentary periods of maximal multidirectional movements (Varley & Aughey, 2013), interspersed with longer periods of low-intensity activity (Bangsbo et al., 2006a). The acyclical activity profile of professional soccer requires a variety of technical actions (e.g., ball touches, passes) to be integrated within players' locomotor performance (Turner & Stewart, 2014). Alongside the concurrent tactical, physiological, and psychological requirements (Bangsbo et al., 2006b), this represents competition demands that are largely multifactorial (Stølen et al., 2005; Dellal et al., 2012). Previous research has demonstrated that the average EFL Championship player covers a total distance of  $11,429.0 \pm 816.0$  m per match, with  $803.0 \pm 227.0$  m being classified as high-speed running (19.8 - 25.1 km·h<sup>-1</sup>) and  $308.0 \pm 139.0$  m categorised as sprinting (> 25.1 km·h<sup>-1</sup>) (Bradley et al., 2013).

As well as the physiological demand of these movement patterns, players must contend with a variety of non-locomotor requirements during match-play (Williams & Ward, 2007). For example, players need to consider their individual positional roles in implementing the team's tactical strategy (Bush et al., 2015), such as executing a high-press to regain ball possession (Bradley & Ade, 2018),

while extracting relevant information from their environment to anticipate what actions teammates and opponents may undertake (Ford et al., 2010). Furthermore, players are required to make appropriate decisions to enact subsequent reactive and proactive behaviours (Williams et al., 2006), with such perceptual-cognitive aspects illustrating the high psychological demands of competition (Krane & Williams, 2006; Williams & Ford, 2008). Although these multiple factors of player performance are interrelated, the key component of successful soccer performance is the ability to score more goals than the opponent within the allotted time period (Lago, 2009; Redwood-Brown et al., 2012). Therefore, professional soccer coaches frequently prioritise technical parameters during training sessions (Morgans et al., 2014a), due to their ability to discriminate between winning, drawing, and losing during competition (Castellano et al., 2012; Carling, 2013).

#### 2.1.1. Technical Performance in Soccer

Technical (i.e., skill-related) performance in soccer has traditionally been described as the learned ability to evoke pre-determined motor skills with maximal proficiency and minimal expenditure of time and energy (Knapp, 1977). McMorris (2004), proposed that technical performance involves the consistent production of learned, sport-specific, goal-oriented movements, which require the interaction and application of cognitive, perceptual, and motor skills in a dynamic environment (Bate, 1996; Williams, 2000). Various discrete technical actions represent important components of soccer performance (Ali, 2011). For example, the ability to accurately pass the ball to a teammate is an essential requirement for all players (Haaland & Hoff, 2003; Rostgaard et al., 2008), with the capacity to dribble past an opponent being associated with talented players (Rösch et al., 2000). Regardless of their specific position, the actions of tackling, heading, crossing, and shooting the ball are necessary competencies that all players must frequently demonstrate (Zeederberg et al., 1996), which are often performed in a sequential manner to achieve a desired performance indicator (e.g., shot on target) (Ali, 2011).

#### 2.1.2. Performance Indicators

Technical performance is often evaluated using performance indicators, defined as the selection and combination of action-related variables that describe aspects of performance (Hughes & Bartlett, 2002;

Taylor et al., 2010). Theoretically, performance indicators should explain match outcomes if they are to provide worthwhile insights into player and team performance (Nevill et al., 2008), with previous researchers (e.g., McGarry, 2009) suggesting that the match score itself may be considered as the definitive indicator of successful performance. Practitioners have adopted 'key' performance indicators as a means of distinguishing position specific indicators that head coaches may associate with success according to their playing philosophy (Hughes et al., 2012; Wright et al., 2012; 2013). However, the addition of this adjective has contributed to ambiguity surrounding the importance of some indicators that are, rather, mere descriptors of performance (Hughes & Bartlett, 2002; O'Donoghue, 2013). To combat such misconceptions, Butterworth et al. (2013), proposed that key performance indicators must be objectively classified as paramount to success, with failure "vastly amplified" in their absence (p. 588). Whereas performance indicators are modifiable, at the discretion of a head coach, the importance of key performance indicators means that they should remain consistent throughout activity, despite the potential influence of situational variables (as discussed further in Section 2.2.1) (Butterworth et al., 2013).

#### 2.1.3. Performance Profiling

Research incorporating performance indicators is necessary for enabling technical performance in soccer to be empirically measured (Parmar et al., 2018). The widespread use of performance indicators by practitioners has enabled researchers to devise technical performance profiles, which describe individual and/or team performance by collecting data pertaining to a multitude of indicators. By quantifying the frequency of discrete technical actions performed during match-play, technical performance profiles may help practitioners to prepare players for peak match demands, to enhance task repetitiveness during training sessions and, potentially, to select appropriate players for a particular match scenario (Liu et al., 2016; Gong et al., 2019).

There are two pertinent techniques for profiling technical performance available within the literature. Each of these techniques (James et al., 2005; O'Donoghue, 2005), collates performance indicators, with pre-determined validity and reliability, that are capable of displaying inter-positional trends throughout a series of performances (Butterworth et al., 2013). Crucially, each technique utilises

confidence intervals (CI) to account for the variability in player performance, which is especially useful for practitioners seeking to establish the degree of performance consistency when selecting between two individuals for one playing position (Butterworth et al., 2013). Practitioners may also utilise CI to determine whether a meaningful change has occurred, or whether performance variability could be a result of measurement error (O'Donoghue, 2013). Performance profiling is beneficial for facilitating the comparison of player data from a specific training session or match, or series of training sessions or matches, against normative values gathered throughout longitudinal monitoring procedures (Akenhead & Nassis, 2016; Rago et al., 2020). Indeed, athletes participating in many team sports (including soccer), perceive performance profiling as useful for promoting self-awareness, enhancing motivation, providing a basis for future goal setting, and evaluating progress over time (Weston et al., 2011), suggesting that such performance enhancing initiatives are welcomed throughout professional sport.

The large financial incentive associated with success in professional soccer has contributed to clubs employing copious methods (e.g., manual coding, third-party data providers, semi-automatic multiple camera tracking systems), which are discussed in detail shortly (Section 2.3), for identifying areas in which they can make marginal gains to yield substantial performance improvements (McParland et al., 2020). Subsequently, the development of technical performance profiles throughout professional soccer (see Section 2.2) has been the subject of numerous academic investigations (e.g., Dellal et al., 2011a; Liu et al., 2016; Aquino et al., 2017; Yi et al., 2019; 2020), providing researchers and practitioners with an objective understanding of the inter-positional differences in players' technical actions during match-play in specific competitions. Much of the available literature concerning technical performance in professional soccer features players competing in the four biggest European domestic leagues (i.e., Spanish Primera División, EPL, German Bundesliga and French Ligue Une) (UEFA, 2020). Each of these competitions has traditionally been characterised by an idiosyncratic style of play (Sarmento et al., 2013), attributed to the historical sociocultural differences that exist between these countries (Sapp et al., 2018). For instance, Spanish Primera División teams tend to emphasise technical proficiency to maintain ball possession (Crolley et al., 2000), whilst EPL soccer features a direct style of play with importance placed upon players' physical attributes (e.g., strength, speed, power) (Dellal et al., 2011a). Clubs competing in the German Bundesliga and French Ligue Une

typically employ stringent defensively-oriented tactical systems (Oberstone, 2011), requiring physically adept players to exploit a counter-attacking style of play (Sapp et al., 2018). Yet, the playing styles and tactical strategies observed throughout these competitions are thought to be evolving (Frick, 2007), due to the heightened frequency of player and coach migration between leagues (Littlewood et al., 2011). For instance, FIFA (2019a) revealed that the highest number of intra-continental player transfers (n = 8,108) was observed within leagues affiliated to UEFA, with such transfers commanding 76.2% of the total value of cumulative transfer fees worldwide ( $\pounds$ 4.22bn).

#### 2.2. Technical Actions in Professional Soccer Match-Play

Several empirical investigations have sought to quantify not only the frequency of discrete technical actions executed during professional soccer match-play (Rampinini et al., 2009; Dellal et al., 2011a; Alberti et al., 2013; Liu et al., 2016; Yi et al., 2020), but also the degree of success associated with these actions (Collet, 2013; Morgans et al., 2014b), and the location on the pitch that such actions are performed (Taylor et al., 2010). Longitudinal research has revealed that the frequency of technical actions executed by professional soccer players during match-play has increased over time. Explicitly, a dataset comprising 22,846 individual player observations from the 2006/2007 to 2012/2013 EPL seasons, unveiled that the frequency of ball touches and passes has risen, by 10.5% and 39.9% respectively, over seven consecutive seasons (Barnes et al., 2014). Bush et al. (2015) furthered Barnes and colleagues' (2014) work, by attributing much of the increase to players who occupy central positions (effect size [ES] = 0.9, moderate). That is, the frequency of passes executed by central defenders ([CD],  $\%^{\text{inc}} = \sim 70.0$ ,  $p \leq 0.001$ ) and central midfielders ([CM], ( $\%^{\text{inc}} = \sim 50.0$ ,  $p \leq 0.001$ ) elevated significantly over this time, with wide defenders (WD), wide midfielders (WM) and strikers (ST), exhibiting small increases ( $\%^{\text{inc}} = \sim 25.0, p \le 0.001$ , ES = 0.5). This increase may be attributed to heightened intra-continental player and coach migration, and subsequent playing philosophy transformations (Sarmento et al., 2013), with the proportion of EPL head coaches coming from overseas increasing by 175.0% during this seven-year period (EPL, 2021). Moreover, retrospective analyses of 44 FIFA World Cup competitions have revealed statistically significant increases in passing rate ( $\overline{X}^{diff}$ 

= 35.4%,  $p \le 0.001$ ) and ball speed ( $\overline{X}^{diff}$  = 15.0%, p = 0.029) between 1966 and 2010 (Wallace & Norton, 2014). Given that the Laws of the Game (International Football Association Board [IFAB], 2020) have generally remained unchanged throughout these time periods (FIFA, 2015), these findings collectively demonstrate that the demands of professional soccer match-play have evolved (Norton & Olds, 2001). This evolution has highlighted the requirement for the modern player to possess sufficient technical proficiency to be successful in competition (Ali et al., 2007; Frencken et al., 2011).

Considering the historical idiosyncrasies associated with each of the four biggest European domestic leagues (Sarmento et al., 2013; Sapp et al., 2018), Dellal et al. (2011a), constructed a technical performance profile that established inter-positional differences (Butterworth et al., 2013) in the frequency of technical actions performed by players during 600 fixtures in the Spanish Primera División and EPL. However, only one performance indicator (ball touches) referred to the frequency of a discrete action that involved only one player at any one time. The remaining indicators either expressed technical actions as a function of time (e.g., duration of ball possession), incorporated a measure of outcome success (e.g., percentage of successful aerial duels), or classified technical actions according to the direction in which they were performed (e.g., passes towards the opponent's goal). Further, Dellal et al. (2011a), failed to provide operational definitions of the examined performance indicators, leaving equivocal variables such as 'duels' open to interpretation. Concerns regarding the lack of transparency (Mackenzie & Cushion, 2013; Carling et al., 2014), lack of consensus (Williams, 2012), and consistent omission of comprehensive operational definitions (Sarmento et al., 2014) have been raised throughout the literature, limiting the potential repeatability of ensuing research (Bradley & Ade, 2018). Nevertheless, reporting the frequency of ball touches performed is relatively unambiguous (O'Donoghue, 2007; 2010), and therefore, facilitates the comparison of this performance indicator throughout various studies (Russell et al., 2016). Accordingly, inter-positional differences in the frequency of ball touches performed by professional soccer players in the Spanish Primera División (n = 1,896) and EPL (n = 4,042) are displayed by Table 2.1.

 Table 2.1: A summary of the inter-positional differences in the frequency of ball touches performed by professional soccer players during match-play in the

 Spanish Primera División and EPL (Dellal et al., 2011a). Data are presented as mean  $\pm$  standard deviation (SD).

	Playing Position								Moon + SD			
Performance Indicator	CD		WD		СМ		WM		ST		Mican ±	50
	Primera División (n = 624)	EPL (n = 1,704)	Primera División (n = 212)	EPL (n = 132)	Primera División (n = 698)	EPL (n = 1,432)	Primera División (n = 100)	EPL (n = 50)	Primera División (n = 262)	EPL (n = 724)	Primera División (n = 1,896)	EPL (n = 4,042)
Ball Touches (f)	$43.4\pm9.7$	$41.2\pm10.1$	54.4 ± 10.7 <b>**</b>	$58.9\pm8.9$	57.3 ± 9.5 *	$55.2\pm8.9$	$55.3\pm9.7$	$56.2\pm8.9$	$41.5\pm7.2$	$43.0\pm7.6$	$251.9\pm7.3$	$254.5\pm8.2$

**N.B.** \* = statistically significant difference ( $p \le 0.005$ ) between competition. \*\* = statistically significant difference ( $p \le 0.001$ ) between competition. SD = standard

deviation. EPL = English Premier League. CD = central defenders. WD = wide defenders. CM = central midfielders. WM = wide midfielders. ST = strikers.

A myriad of investigations have sought to examine the differences in players' technical actions between the aforementioned European domestic competitions (e.g., Dellal et al., 2011a; Oberstone, 2011; Alberti et al., 2013; Collet, 2013; Lago-Peñas et al., 2016; Sapp et al., 2018). However, whilst some studies have utilised third-party data providers ([see Section 2.3.2], Lago-Peñas et al., 2016) or semi-automatic multiple camera tracking systems ([as discussed in Section 2.3.3], Dellal et al., 2011a) to measure technical performance, others have relied upon official competition resources ([e.g., www.premierleague.com], Alberti et al., 2013) or publicly available online databases ([e.g., www.whoscored.com], Sapp et al., 2018). As discussed further in Section 5.3, methodological concerns regarding inconsistent methods of data collection and statistical analysis have limited the comparability of previous research (Yi et al., 2019). Therefore, the standardised method of quantifying technical performance during UEFA Champions League match-play, which is an inter-league competition contested between top division clubs throughout Europe, represents an efficacious source of data for scientific study. Subsequently, the work of Yi and colleagues' research group has provided a contemporary understanding of the frequency of technical actions performed by professional players at the pinnacle of European soccer.

In the first of two studies examining more than 1,000 UEFA Champions League fixtures over an 8-season period, Yi et al. (2019), used generalised mixed linear modelling to quantify the differences in players' technical actions from the four prominent European leagues during UEFA Champions League match-play. As displayed below (Table 2.2), players from each of these domestic competitions typically performed  $61.5 \pm 20.8$  ball touches,  $44.3 \pm 19.2$  passes,  $1.1 \pm 2.6$  crosses,  $1.0 \pm 1.5$  shots and  $1.5 \pm 2.2$  clearances per match. Using the term 'releases', adapted from the term 'distributions' previously applied within the literature to describe the cumulative total number of passes, crosses, shots and clearances performed (Russell et al., 2013; Harper et al., 2014), this equates to each player executing  $48.0 \pm 25.5$  releases per match. **Table 2.2:** A summary of the frequency of technical actions performed by players from four prominent European domestic leagues during UEFA Champions

 League match-play (Yi et al., 2019). Data are presented as mean ± SD.

Performance Indicator					
	Primera División (n = 2,597)	EPL (n = 2,303)	Bundesliga (n = 2,021)	Ligue Une (n = 1,356)	Mean ± SD
Ball Touches (f)	$61.6 \pm 20.8$	$61.3 \pm 20.7$	62.3 ± 21.0	$60.6 \pm 20.6$	$61.5 \pm 20.8$
Passes (f)	$44.9\pm19.4$	$43.9 \pm 19.1$	$45.6\pm19.6$	$42.9\pm18.8$	$44.3 \pm 19.2$
Crosses (f)	$1.0\pm2.5$	$1.0 \pm 2.5$	$1.2 \pm 2.7$	$1.3 \pm 2.8$	1.1 ± 2.6
Shots (f)	$1.0 \pm 1.4$	$0.9 \pm 1.4$	$1.2 \pm 1.6$	$1.0 \pm 1.5$	1.0 ± 1.5
Clearances (f)	$1.5 \pm 2.2$	$1.6 \pm 2.2$	1.5 ± 2.2	1.5 ± 2.1	1.5 ± 2.2
Releases (f)	$48.4\pm25.5$	$47.4\pm25.2$	$49.4\pm26.0$	$46.6 \pm 25.2$	48.0 ± 25.5

**N.B.** SD = standard deviation. EPL = English Premier League.

#### 2.2.1. Effect of Situational Variables

A situational variable encompasses any extraneous variable that impacts player performance at a behavioural level (Gómez-Ruano et al., 2013). Due to the complex and highly dynamic nature of professional soccer (Liu et al., 2015), match performance cannot be generalised in all contexts. Therefore, the frequency of technical actions executed during match-play may be influenced by multiple modifiable and non-modifiable contextual (e.g., fixture schedule, season phase) and environmental (e.g., altitude, temperature) variables (Trewin et al., 2017; Impellizzeri et al., 2019; Stodter & Cushion, 2019). The inclusion of situational variables when devising technical performance profiles reveals further detail surrounding players' match behaviours (McGarry, 2009; Bradley et al., 2014), by providing additional information regarding the nature of competition at any given time (Dalton-Barron et al., 2020). Trewin and colleagues' (2017), suggested that both types of situational variable may impact player performance, with their exclusion during performance profiling yielding a one-dimensional view of a match (Paul et al., 2015). Situational variables might be deemed important when considering the relatively low-scoring nature of soccer, and lack of control over match fluctuations compared with other invasion games (e.g., basketball, netball), whereby practitioners are able to influence match momentum by utilising strategic time-outs (Wright et al., 2014).

Previous research that has examined the influence of situational variables on players' technical performance during match-play typically incorporates the creation of a technical performance profile (Liu et al., 2016; Yi et al., 2020). Such investigations enhance scholarly understanding of the frequency of technical actions executed by professional soccer players during match-play. Therefore, interpositional differences in the frequency of technical actions performed during 380 Spanish Primera División matches that took place during the 2012/2013 season are displayed by Table 2.3 (Liu et al., 2016).

División match-play (Liu et al., 2016). Data are presented as mean  $\pm$  SD. **Playing Position** Performance Mean ± SD Indicator WD (n = 1,289)WM (n = 676)ST (n = 532)CD (n = 1,393)CM (n = 1,398)

 $58.0\pm15.6$ 

 $36.0\pm12.6$ 

 $5.4\pm4.4$ 

 $3.0\pm2.3$ 

 $0.7 \pm 1.0$ 

 $45.1\pm20.2$ 

 $51.0\pm17.0$ 

 $35.0\pm15.6$ 

 $1.5\pm2.0$ 

 $3.2\pm2.0$ 

 $0.6\pm1.2$ 

 $40.3\pm20.7$ 

 $60.7 \pm 18.8$ 

 $41.3\pm17.3$ 

 $2.2\pm2.3$ 

 $1.7 \pm 1.4$ 

 $2.6\pm2.0$ 

 $47.9\pm23.1$ 

 $72.50 \pm 24.0$ 

 $57.5\pm24.0$ 

 $1.7 \pm 2.7$ 

 $1.1 \pm 1.2$ 

 $1.5 \pm 1.8$ 

 $61.8\pm29.6$ 

Table 2.3: A summary of the inter-positional differences in the frequency of technical actions performed by professional soccer players during Spanish Primera

 $69.0\pm19.5$ 

 $40.0\pm17.0$ 

 $2.7\pm2.5$ 

 $0.5\pm0.8$ 

 $3.3 \pm 2.3$ 

 $46.5\pm22.6$ 

Ball Touches (f)

Passes (f)

Crosses (f)

Shots (f)

Clearances (f)

Releases (f)

 $53.0\pm18.0$ 

 $\mathbf{38.0} \pm 17.5$ 

 $0.1\pm0.4$ 

 $0.5\pm0.8$ 

 $7.2\pm4.0$ 

 $45.8\pm22.6$ 

<b>N.B.</b> $SD =$ standard deviation. $CD =$ central defended	ers. WD = wide defenders. CM = central midfielders. WM	M = wide midfielders. ST = strikers.

Further to their work published in 2019, Yi et al. (2020), devised a performance profile that considered the effects of three situational variables (i.e., match outcome, qualification status, match location) on the inter-positional differences in the frequency of technical actions performed during the group and knock-out stages of the UEFA Champions League. This investigation failed to report the statistical magnitude of these inter-positional differences prior to considering the influence of the previously specified contextual variables. Yet, the longitudinal dataset provided by Yi et al. (2020), contributes the most contemporary understanding of the frequency of technical actions executed during professional soccer match-play to date, serving as a useful resource for evidence-based practitioners to refer to when prescribing training activities. As displayed by Table 2.4, CM typically performed more ball touches, and cumulative releases (Russell et al., 2013; Harper et al., 2014), than all other playing positions during match-play. Specifically, players who occupied this position executed more ball touches than CD ( $\overline{X}^{diff} = 6.4$ ), WD ( $\overline{X}^{diff} = 6.5$ ), WM ( $\overline{X}^{diff} = 12.8$ ) and ST ( $\overline{X}^{diff} = 15.9$ ). Further, CM performed more releases than CD ( $\overline{X}^{diff} = 4.4$ ), WD ( $\overline{X}^{diff} = 7.0$ ), WM ( $\overline{X}^{diff} = 11.3$ ) and ST ( $\overline{X}^{diff} = 17.0$ ).

Table 2.4: A summary of the inter-positional differences in the frequency of technical actions performed during UEFA Champions League match-play (Yi et

al., 2020). Data are presented as mean  $\pm$  SD.

Performance Indicator	Playing Position					Maan + SD
	CD (n = 3,632)	WD (n = 3,429)	CM (n = 4,044)	WM (n = 1,565)	ST (n = 1,767)	Mean ± SD
Ball Touches (f)	$61.5\pm20.5$	61.4 ± 18.7	$67.9 \pm 23.2$	$58.2 \pm 20.8$	$52.1\pm20.3$	$60.2\pm20.7$
Passes (f)	$47.5\pm20.7$	$44.4\pm17.0$	53.2 ± 22.9	41.0 ± 19.3	$35.3\pm16.8$	$44.3\pm19.3$
Crosses (f)	0.8 ± 1.9	2.5 ± 2.7	$1.5 \pm 2.5$	$2.6 \pm 3.0$	$2.3\pm2.9$	$1.9 \pm 2.6$
Shots (f)	$0.6 \pm 0.9$	$0.5\pm0.8$	$1.2 \pm 1.5$	$1.9 \pm 1.7$	$2.9\pm2.0$	$1.4 \pm 1.4$
Clearances (f)	4.7 ± 3.5	3.5 ± 2.8	$2.0 \pm 2.8$	1.1 ± 1.6	$0.6\pm0.9$	$2.4\pm2.3$
Releases (f)	$53.6\pm27.0$	51.0 ± 23.4	$57.9\pm29.5$	$46.6 \pm 25.7$	$41.0\pm22.7$	$50.1 \pm 25.7$

**N.B.** SD = standard deviation. CD = central defenders. WD = wide defenders. CM = central midfielders. WM = wide midfielders. ST = strikers.

#### 2.2.2. Effect of Neuromuscular Fatigue

Laboratory and field-based soccer simulation protocols have been validated for replicating multiple performance metrics observed during match-play (Stone et al., 2011; Robineau et al., 2012; Page et al., 2015). Researchers have utilised such protocols to consistently demonstrate the detrimental impact of neuromuscular fatigue on indices of technical performance. For instance, Russell et al. (2011) observed fatigue-related decrements to the shooting accuracy ( $\%^{\text{diff}} = -25.5$ , p = 0.035) and passing speed ( $\overline{X}^{\text{diff}} =$ 0.8 m·s<sup>-1</sup>, p = 0.039) of EFL Championship soccer players following an adapted 90-minute version of the Loughborough Intermittent Shuttle Test (Nicholas et al., 2000). This was analogous with the findings of Stone and Oliver (2009), who reported significant reductions to semi-professional players' dribbling time ( $\%^{\text{inc}} = 4.5$ , p = 0.009) and shooting accuracy ( $\overline{X}^{\text{diff}} = -7.6$  au, p = 0.012) as a result of 45 minutes of the same soccer-specific exercise protocol (Nicholas et al., 2000). Moreover, similar protocols have hindered players' maximal shank angular velocity and resultant ball velocity ( $\overline{X}^{diff}$  = -2.9 m·s<sup>-1</sup>,  $p \le 0.001$ ) (Kellis et al., 2006), as well as maximal ball velocity ( $\eta^2 = -0.39$ ,  $p \le 0.005$ ) (Ferraz et al., 2019), which potentially reduces players' chances of scoring by giving goalkeepers more time to react to a slower moving ball (Dörge et al., 2002). Such findings likely relate to the mechanics of a soccer kick. That is, the repeated eccentric contractions, and rapid eccentric-to-concentric transfer, required during kicking, promotes structural muscular damage and inflammation (Guex & Millet, 2013). In particular, the backswing phase of a soccer kick requires a high-force eccentric contraction of the knee extensors (Brophy et el., 2007) to decelerate knee flexion and initiate the forward swing phase (Orchard et al., 1999).

Previous research that has investigated the effect of neuromuscular fatigue on indices of technical performance has required the use of complex, laborious, and expensive laboratory-based methods (Waldron & Highton, 2014). For example, Russell and colleagues (2011), used advanced motion capture methods, which comprised eight semi-fixed cameras sampling at 100 Hz recording the position of 18 body-worn optical markers, to measure the three outcome variables of precision, percentage success, and mean ball speed. Although the specific number of data points analysed was not stated, the complicated methods used to determine these variables (as described in detail by Russell et

al. [2010]) required intricate synchronisation and digitisation of video footage. Further, Stone and Oliver (2009) determined players' dribbling ability using a laser timing gate system, with shooting accuracy ascertained through nine players collectively performing in excess of 900 repetitions of the Loughborough Soccer Shooting Test (Ali et al., 2007). Kellis et al. (2006), conducted their three-dimensional kinematic analyses using two video cameras that tracked the location of 12 anatomical markers, and two ball-mounted markers, whilst Ferraz et al. (2019) quantified ball velocity using a hand-held Doppler radar speed gun. Such sophisticated methods are generally unavailable outside of the laboratory, leaving the fast working professional soccer practitioners unable to longitudinally monitor the impact of neuromuscular fatigue on players' technical performance (Coutts, 2016; Malone et al., 2019). In this setting, practitioners may benefit from more automotive wearable technologies that facilitate field-based data collection in a timely manner (see Section 2.5).

#### 2.3. Monitoring Technical Performance in Professional Soccer Match-Play

The evident longitudinal increases in the frequency of technical actions executed by professional soccer players during match-play (Section 2.2) (Barnes et al., 2014, Bush et al., 2015) has emphasised the requirement for practitioners to accurately quantify technical performance (Hughes & Franks, 2004). In this context, notational analysis has been described as an objective method of recording player performance, allowing the key elements of performance to be quantified in a consistently valid and reliable manner (Nevill et al., 2008). Sitting alongside time-motion analysis, under the performance analysis umbrella (Mackenzie & Cushion, 2013; Sarmento et al., 2014), notational analysis has traditionally focussed upon the systematic observation of technical-related facets of player performance that occur in their natural context (i.e., match-play) (O'Donoghue & Mayes, 2013; Sampaio & Leite, 2013). Notational analysis quantitatively records the frequency of specific technical actions performed (Taylor et al., 2008), which tends to incorporate a qualitative appraisal of the effectiveness of such actions (Carling et al., 2005).

During a historical review of the development and progression of literature published in the field of sports science over a 25-year period, Nevill et al. (2008) noted a substantial upsurge in the application of performance analysis in numerous sports around the 1980s (e.g., Reilly, 1976; Sanderson
& May, 1977; Sanderson, 1983). Previously, both performance analysis research and practice involved the handwritten formalisation of movement (i.e., hand notational analysis) (Hughes & Franks, 2004). However, despite early attempts to quantify player performance during invasion games (e.g., Messersmith & Corey, 1931; Reep & Benjamin, 1968), the expansion of performance analysis was concomitant with the development of audio-visual and information technologies (David, 2005), such as the widespread use of portable video cameras and computers (Teschke et al., 2009), alongside the initial publication of the Journal of Sports Sciences (Nevill et al., 2008). Having been accepted as a legitimate sub-discipline by the British Association of Sport and Exercise Sciences in 1988, and with the advent of a dedicated professional body (i.e., International Society of Performance Analysis of Sport) alongside the introduction of global conferences (e.g., World Congress of Performance Analysis in Sport) and specialised scientific journals (e.g., International Journal of Performance Analysis in Sport), performance analysis has gained a prominent place in the scientific literature (Sarmento et al., 2014) and is presently viewed as an important part of the multidisciplinary sports science service available to support players and head coaches (Butterworth et al., 2013; Halson et al., 2019).

Previous research has sought to address both the applied and theoretical perspectives of performance analysis (McGarry, 2009), the role that a performance analyst undertakes in professional soccer (Wright et al., 2013), player and head coach engagement (Wright et al., 2016) and perceptions of the discipline (Reeves & Roberts, 2013; Francis & Jones, 2014; Nelson et al., 2014), and the coach-analyst relationship (Bateman & Jones, 2019). From a theoretical standpoint, the overriding purpose of performance analysis is to provide accurate supplementary information to key stakeholders by gathering an objective audit of the behaviours performance analyst working in professional soccer involves monitoring players' technical performance according to an abundance of pre-determined performance indicators (Section 2.1.2) (Hughes et al., 2001). Given the aforementioned technological advancements that have occurred over recent decades, performance analysts have utilised a number of approaches for quantifying the frequency of technical actions executed during match-play. Each of these approaches has distinct considerations regarding their benefits, drawbacks, validity, reliability, availability, and financial feasibility, which are discussed in detail throughout the forthcoming sections.

### 2.3.1. Manual Coding

## 2.3.1.1. Overview

The manual coding of video footage (i.e., computerised notational analysis) has been described as the process by which a performance analyst may utilise electronic software to physically highlight the frequency of specific actions that occur during a match (Wright et al., 2013). There are many examples of software packages that performance analysts may utilise to monitor technical performance during match-play (e.g., Fulcrum Angles, Dartfish, Nacsport) (Robertson, 2020). However, 59.0% and 87.5% of the respective samples of Wright et al. (2012) and Wright et al. (2013) identified SportsCode as their most widely used software package, contributing to this programme featuring heavily throughout academic investigations concerning the validity and reliability of manual coding as a method of measuring technical performance (Reed & Hughes, 2006; González-García et al., 2016; Francis et al., 2019). Notwithstanding the specific software package used, this approach provides stakeholders with a wealth of descriptive data that typically pertains to four of the six traditional 'servants' purported by Kipling (1902). That is, manual coding by a human performance analyst enables the 'who?' (i.e., the player(s) involved), 'what?' (i.e., the specific type, and outcome, of the action performed), 'where?' (i.e., the location on the pitch that the action occurred), and 'when?' (i.e., the time during an activity that the action took place) to be established.

Manual coding is a relatively inexpensive method of quantifying technical performance, that is available in both the training and competition environments. The comprehensive dataset yielded through manual coding provides head coaches with an abundance of feedback upon which to make informed decisions regarding the nature of training activities or team preparation (O'Donoghue, 2007). However, given that objective feedback plays an important role during the process of performance improvement (Nelson & Groom, 2012), it is crucial that the data collected through manual coding is consistently valid and reliable (Nevill et al., 2008). The analytical goal of achieving between 80.0% - 85.0% inter- and intra-operator reliability has been historically accepted (Van Der Mars, 1989). Yet, in light of the contemporary technological advancements that are discussed shortly, such thresholds may now be considered statistical artefacts.

#### 2.3.1.2. Validity and Reliability

The use of manual coding as a method of measuring the frequency of technical actions performed should always be preceded by an examination of the validity and reliability of the individual(s) responsible for collecting the required data (O'Donoghue, 2007). As such, the International Journal of Performance Analysis in Sport have stipulated this as an essential requirement for original research articles to be considered for publication, enabling researchers and practitioners to interpret the results of a given investigation with an appreciation of the associated measurement error (O'Donoghue, 2007). This requirement has contributed to previous research demonstrating that manual data collection through computerised coding can provide an efficacious method of measuring the frequency of technical actions performed during match-play in many sports (González-García et al., 2016; Francis et al., 2019; Gong et al., 2019). For instance, González-García et al. (2016), reported very good agreement (Cohen's Kappa [K] = 0.85 - 0.96) (Altman, 1991; Viera & Garrett, 2005; O'Donoghue, 2010) between four performance analysis system operators, with low overall typical error of measurement (TEM) values of between 0.1% - 0.2%. Moreover, Francis et al. (2019), noted very good agreement (K = 0.98 - 1.00) and low TEM values (0.0% - 1.5%) between two system operators, with those examined by Gong et al. (2019) displaying very good intra-operator (K = 0.89 - 0.97) and inter-operator (K = 0.87 - 0.93) agreement combined with low TEM values (0.0% - 0.3%). These investigations collectively demonstrate that manual coding by a human performance analyst, using the specific data collection instrument during each respective study, can possess sufficient validity and reliability for quantifying the frequency of technical actions performed in various sporting scenarios. However, a clear, welldesigned, performance analysis instrument (see Figure 2.1 for a soccer-specific example), accompanied by precise operational definitions, is required to facilitate straightforward data collection and subsequent practical applications of manual coding (Gong et al., 2019).

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**Figure 2.1:** An exemplar soccer-specific performance analysis instrument used to manually code the frequency, pitch location, and outcome of six possession-related performance indicators (adapted from O'Donoghue & Holmes, 2015).

A common theme throughout these studies is the degree of experience required for system operators to achieve sufficient validity and reliability. The operators investigated by González-García et al. (2016), possessed 14.69  $\pm$  1.92 years of playing experience prior to their 4.64  $\pm$  4.04 years of coaching experience, and underwent an extensive 12-hour training regime to become familiar with the data collection instrument prior to the study. Those examined by Francis et al. (2019), had 19.33  $\pm$  0.58 years of coaching experience, with a similar familiarisation period of 10 hours preceding the investigation. Despite possessing comparably less experience ( $\overline{X} = 1.75 \pm 0.29$  years) than prior studies, Gong et al. (2019) described their system operators as well-trained, with it being suggested that those responsible for manual coding must undergo systematic and consistent practice, using the required

performance analysis instrument (O'Donoghue, 2010), to diminish the potential for human error adversely impacting the validity and reliability of the data collected through this method. Reporting data which may contain human measurement error, which is one of the seven historical scientific dishonesties (Thomas & Nelson, 1996), risks key stakeholders making flawed decisions regarding training strategies or team preparation based on potentially erroneous findings (O'Donoghue, 2007; Reeves & Roberts, 2013).

## 2.3.1.3. Considerations

The main issue associated with the manual coding of video footage by a performance analyst is the significant amount of human resources required to produce such a detailed dataset (Nelson & Groom, 2012), in a timely manner (Carling et al., 2014; Robertson, 2020), that is consistently valid and reliable (O'Donoghue, 2007; Nevill et al., 2008). The aforementioned system operators collectively possessed a mean of  $13.47 \pm 0.95$  years of experience, alongside extensive training regimes, in order to attain acceptable levels of validity and reliability (González-García et al., 2016; Francis et al., 2019; Gong et al., 2019). Moreover, a high proportion (n = 9, 28.1%) of Wright and colleagues' (2013) sample of practitioners working in professional soccer reported spending more than six hours to complete their post-match analyses. Within a typical training week, practitioners must also allocate time to conduct post-match feedback sessions (n = 39, 81.3%), pre-match opposition analysis (n = 38, 79.2%), and live within-match analysis (n = 38, 79.2%) (Wright et al., 2013). Given that insufficient human resources are a substantial barrier to effective player monitoring procedures (Akenhead & Nassis, 2016), outsourcing the process of manual coding to third-party data providers (Section 2.3.2) or investing in state-of-the-art camera systems (as discussed in Section 2.3.3) and/or wearable microtechnology (Section 2.3.4) may be practically advantageous for practitioners working in the demanding environment of professional soccer (Bourdon et al., 2017).

#### 2.3.2. Third-Party Data Providers

## 2.3.2.1. Overview

Third-party sports data providers present organisations with an alternative method to relying on manual data collection by performance analysts to quantify technical performance. There are numerous companies (e.g., InStat, StatsBomb, STATS Perform, Wyscout) who collect, analyse, and distribute data relating to copious performance indicators (Liu et al., 2013). Founded in 1996 and now described as a "media powerhouse" (Frodl, 2015, p. 61), OPTA Sports are the largest private data provider available to broadcasters, governing bodies, and professional clubs across more than 40 sports worldwide (Yarrow & Kranke, 2016). To extend their performance analysis provision, elite soccer clubs tend to employ dedicated data specialists, often with atypical backgrounds in sectors such as mathematics and theoretical physics, to embark upon focussed match analysis (Lewis, 2014). Indeed, OPTA Sports was identified as the second-most widely used tool that 32.0% of 46 experienced soccer coaches noted as having access to (Wright et al., 2012). The data provided by OPTA Sports has been central to academic investigations concerning players' technical performance during match-play (e.g., Oberstone, 2009; 2010; 2011; Liu et al., 2016; Yi et al., 2019; 2020; Errekagorri et al., 2020). However, an understanding of the validity and reliability of OPTA Sports is required for the data to be used with assurance by practitioners working in soccer clubs that devote significant financial resources by subscribing to the provider (O'Donoghue, 2007).

#### 2.3.2.2. Validity and Reliability

Given the evident popularity and diverse demographic of OPTA Sports' clientele, it might be considered surprising that just one study has challenged the efficacy of the data provided by the company. Liu et al. (2013), undertook the only independent examination of the validity and reliability of the performance analysis instrument, known as OPTA Client System, used by OPTA Sports' performance analysts to quantify players' technical actions during match-play. This investigation involved four well-trained operators ( $\overline{X} = 2.13 \pm 0.85$  years of experience), who had undertaken a 'rigorous' familiarisation regime, to independently code technical actions from just one Spanish Primera División fixture. This study revealed that the four independent operators agreed upon 1,509 technical actions performed by outfield players (K = 0.92 - 0.94), and 95 technical actions executed by goalkeepers (K = 0.86 - 0.92), resulting in low TEM values of between 0.1% - 0.2%. Given the absence of subsequent investigations that may oppose Liu and colleagues' (2013) findings, the OPTA Client System may be cautiously considered a valid and reliable method of quantifying the frequency of technical actions performed during professional soccer match-play (Liu et al., 2013).

## 2.3.2.3. Considerations

Third-party sports data providers are an expensive method of measuring technical performance. For example, a basic package of OPTA Sports' services, granting access to data from only one European domestic competition, requires a minimum annual subscription fee of £12,000 (OPTA Sports, 2017). Comprehensive packages encompassing 20 competitions demand a significant financial commitment of up to £81,500 per annum (OPTA Sports, 2017); figures likely to have risen over the previous four years. Such monetary obligations may be simply unfeasible for many professional clubs (O'Reilly et al., 2018), especially in the EFL, given the dwindling annual revenues procured when competing lower down the English soccer pyramid (Deloitte, 2020).

Practitioners working in professional sport recently identified "immediate" and "time-efficient" feedback as important prerequisites of player monitoring procedures (Starling & Lambert, 2018, p. 781). However, technical performance insights provided by OPTA Sports are subject to a 24-hour process of quality control, whereby the in-stadium data collection is checked by criterion data analysts located in offices worldwide (OPTA, 2021). This may reduce the usefulness of this method, with some professional soccer players also preferring to receive objective post-match feedback immediately to inform their post-match reflection (Wright et al., 2016). By providing objective post-match feedback promptly, at the point at which an individual's recollection of their performance may be clearest (McArdle et al., 2010), players are not afforded the time to dwell on potentially poor performances (Wright et al., 2016). This enables their attention to be placed upon the next opponent as soon as possible (Carling et al., 2014), something particularly important at the professional level, given the limited time in which players are required to complete pre-match opposition analysis during periods of fixture congestion (Wright et al., 2013; 2014; Morgans et al., 2014b). Therefore, practitioners may seek

alternative methods of monitoring technical performance during professional soccer match-play, such as that discussed shortly (Section 2.3.3), which does not entail such delays.

### 2.3.3. Semi-Automatic Multiple Camera Tracking Systems

# 2.3.3.1. Overview

The use of semi-automatic multiple camera tracking systems has evolved considerably since Van Gool et al. (1988) pioneered this method in the sporting environment more than 30 years ago. Now considered a sophisticated means of quantifying player performance (Castellano et al., 2014), substantial technological developments have enabled computer-aided technologies to concurrently track the movements of soccer players, match officials, and the soccer ball to measure plenteous time-motion, technical, and tactical parameters (Carling et al., 2012). Consequently, the introduction of such technology has equipped practitioners with large volumes of data, in timescales unrivalled by previous monitoring methods, providing head coaches with the potential to refine the training process (Castellano et al., 2012; Drust, 2019).

The amalgamation of the two prominent suppliers of this technology (Amisco Pro<sup>®</sup> and ProZone Sports<sup>®</sup>) in 2011, to form a "global industry leader in sports data and performance analytics" (Frodl, 2015, p. 61), has resulted in semi-automatic multiple camera tracking systems being installed at the stadia of all 20 EPL clubs, as well as countless venues worldwide (Taberner et al., 2020). Subsequently, researchers have utilised these systems throughout the literature examining time-motion (e.g., Abt & Lovell, 2009; Di Salvo et al., 2009; 2010; Carling et al., 2010; 2011; 2012; Di Mascio & Bradley, 2013; Anderson et al., 2015; 2016; Carling et al., 2016; Chmura et al., 2017), technical (e.g., Taylor et al., 2008; Lago, 2009; Russell et al., 2013), and the interaction between time-motion and technical parameters (e.g., Dellal et al., 2010; 2011a; 2013; Barnes et al., 2014; Morgans et al., 2014b; Bush et al., 2015; Ade et al., 2016) during match-play. A ProZone<sup>®</sup> system requires eight stable synchronised cameras, sampling at a rate of 25 Hz, to be permanently installed in optimally calculated positions at the top of soccer stadia (Randers et al., 2010; Fradua et al., 2013). As depicted by Figure

2.2 below, these eight cameras are positioned to ensure that each pitch location is covered by two camera angles for accuracy, resolution, and to protect against occlusion (Di Salvo et al., 2006).



**Figure 2.2:** A schematic of the position and pitch coverage provided by eight stable synchronised cameras, installed at Manchester United's Old Trafford stadium, that comprise a ProZone<sup>®</sup> semi-automatic multiple camera tracking system (adapted from Di Salvo et al., 2006).

## 2.3.3.2. Validity and Reliability

Many studies have sought to establish the validity and reliability associated with both Amisco Pro<sup>®</sup> (Zubillaga et al., 2009; Randers et al., 2010) and ProZone<sup>®</sup> (Bradley et al., 2007; 2010; Di Salvo et al., 2006; 2009; Harley et al., 2011) technologies. However, the majority of these studies focussed upon time-motion variables, such as comparing ProZone<sup>®</sup> data with timing gate recordings during different running tasks (Di Salvo et al., 2006), or comparing these systems with MEMS (Randers et al., 2010; Harley et al., 2011). A review of the published literature, which utilises such systems (Castellano et al., 2010)

2011), identified only one study that provides evidence in support of manufacturers' claims regarding their validity and reliability for measuring technical actions (Edgecomb & Norton, 2006). That is, Bradley et al. (2007) compared the data gathered by 14 independent ProZone<sup>®</sup> system observers during one EPL match in the 2006/2007 season. This investigation reported that 2,552 events from the match were correctly identified by ProZone<sup>®</sup> observers which, alongside the low TEM of  $\leq 0.01$  s for event time and 3.6 m for event location, resulted in very good validity and reliability for measuring the frequency (K = 0.99), and player(s) involved (K = 0.99), in technical actions performed during match-play (Bradley et al., 2007).

### 2.3.3.3. Considerations

Although semi-automatic multiple camera tracking systems may alleviate concerns related to human resources (Wright et al., 2013; Carling et al., 2014; Akenhead & Nassis, 2016; Bourdon et al., 2017), and provide key stakeholders with feedback in a time-efficient manner (Wright et al., 2016; Starling & Lambert, 2018), this method of measuring technical performance is not without limitation. As described in detail by Di Salvo et al. (2006), these systems require an intricate arrangement of high-specification computer equipment to synchronise and filter the data captured by eight separate cameras into one exportable dataset, obligating a significant financial investment from organisations (Castellano et al., 2014; Lago-Peñas & Sampaio, 2015). For clubs below the top division of English soccer, who may perceive inexpensive as a desirable prerequisite of a player monitoring system (Starling & Lambert, 2018), the cost of these systems can be presumed as a barrier to their implementation (Brink et al., 2018; Deloitte, 2020). This has likely contributed to the relatively low proportion of practitioners reporting access to Amisco Pro<sup>®</sup> ( $\overline{X} = 27.1\%$ ) and ProZone<sup>®</sup> ( $\overline{X} = 35.4\%$ ) technologies (Wright et al., 2013). The subsequent lack of systematic coverage throughout soccer clubs has led to inconsistencies in the data available at different levels of the English soccer pyramid (Drust, 2019), limiting the potential for research comparing player performance across the domestic leagues in England.

The eight semi-automatic cameras that comprise these tracking systems are positioned around the roof of soccer stadia which, in the EPL, is generally at a towering height. However, with most EFL stadia typically being considerably smaller, such as AFC Wimbledon's Plough Lane stadium reaching just 12.5 m, clubs competing at this level may lack the height required to prevent occlusion and utilise these systems effectively (Di Salvo et al., 2006; Rein & Memmert, 2016). Moreover, with the exception of some ultra-modern facilities in England, such as the Academy Stadium situated at Manchester City's Etihad Campus, the training centres of English soccer clubs also fail to possess the necessary infrastructure to facilitate the implementation of semi-automatic multiple camera tracking systems in this environment (Buchheit & Simpson, 2017). This may present a complication for practitioners, in considering the problematic nature of quantifying performance with different systems in different environments (see Section 5.3) (Buchheit et al., 2014b; Taberner et al., 2020).

#### 2.3.4. Microelectromechanical Systems

### 2.3.4.1. Overview

The previous 20 years has seen a substantial increase in the use of wearable microtechnology for monitoring professional soccer player performance during training and match-play (Zhou et al., 2016; Malone et al., 2020). Now, the use of MEMS has provided key stakeholders with access to more information regarding player performance than ever before (Cummins et al., 2013; Coutts, 2014a; Bartlett et al., 2017). The widespread acceptance of wearables has also contributed to an exponential rise in original research articles using such technology available in PubMed between 2001 and 2018  $(\%^{inc} = 4,433.3)$  (Malone et al., 2020). Such devices collect data pertaining to an array of variables, with the most appropriate variables directly relating to the competition demands of a particular sport (Impellizzeri et al., 2019). Consequently, those tasked with monitoring player performance must carefully select suitable metrics that answer the questions of key stakeholders (Buchheit, 2017a), by considering how players' data will be consistently collected, the potential limitations of certain variables, and how this data will be effectively communicated (Thornton et al., 2019; Nosek et al., 2021). Monitoring performance using MEMS permits decisions concerning player preparation to be made objectively (Malone et al., 2017; Rago et al., 2020), and enables the simultaneous assessment and manipulation of training activities (Barrett, 2017; Weaving et al., 2017). This process is important for arranging training stimuli that promote physiological adaptations, whilst limiting the risk of injury

(Colby et al., 2014) and, therefore, enhances the likelihood of eliciting favourable training outcomes, such as improvements in physical qualities or technical proficiency (Impellizzeri et al., 2005).

Practitioners have traditionally reported the frequency of specific technical actions, or the distance covered along a time-motion continuum of walking to sprinting, without accounting for players' specific roles within the team's tactical strategy (Bush et al., 2015). However, the advent of specialised computer software packages (e.g., Catapult Vision) enables the manually coded video footage of technical performance (as discussed in Section 2.3.1) to be combined with the corresponding time-motion data provided by MEMS, in order to provide plausible situational explanations for player performance (Bradley & Noakes, 2013). However, the process of amalgamating one manual method of measuring players' technical actions (i.e., manual coding), with one automotive method of conducting time-motion analysis (i.e., MEMS), fails to mitigate the limitations of manual coding as already discussed. Therefore, to facilitate the desirable multidimensional integrated approach of monitoring player performance (Bradley & Ade, 2018), practitioners should explore the use of automotive technologies (e.g. wearable IMUs) for monitoring sport-specific technical actions (Chapter 4).

The IMU components found within MEMS devices (i.e., accelerometers, gyroscopes and magnetometers) are capable of quantifying movement in the anterior-posterior, mediolateral, and longitudinal axes, respectively (Krasnoff et al., 2008; Chambers et al., 2015). Prior applications of wearable IMUs have demonstrated the ability for practitioners to efficiently measure the frequency and magnitude of gross fatiguing sport-specific actions in the field, something previously restricted to the laboratory (Dixon et al., 2018; Kyprianou et al., 2019). Chambers and colleagues (2015) identified a variety of studies that have utilised single or multiple IMUs to measure such sport-specific movements in individual (n = 8), team (n = 7), water (n = 8), and snow (n = 5) sports. However, this systematic review revealed no prior attempts to utilise MEMS to measure soccer-specific technical actions. Consequently, the following paragraph shall discuss previous applications of wearable microtechnology for quantifying sport-specific actions in sports other than soccer.

Ahmadi et al. (2009) measured determinants of a tennis serve using a Kionix IMU, with the inertial components within Catapult's MinimaxX<sup>TM</sup> S4 being used by researchers to monitor tackling in rugby league (Gabbett et al., 2010) and Australian rules football (Gastin et al., 2013; 2014). Dadashi

and colleagues' research group quantified front crawl characteristics during swimming with a Physilog<sup>®</sup> IMU (Dadashi et al., 2012; 2013), with both the Physilog<sup>®</sup> IMU and MinimaxX<sup>™</sup> S4 being used to monitor segmental coordination in skiing (Chardonnens et al., 2012; 2013) and snowboarding (Harding et al., 2008) respectively. Contemporary research has seen Catapult's MinimaxX<sup>™</sup> S4 (McNamara et al., 2015), and OptimEye S5 devices (Jowitt et al., 2020), being used to automatically detect fast bowling deliveries in cricket (McGrath et al., 2019). Finally, scholars have utilised a bespoke IMU to determine the characteristics of a spike action in volleyball (Wang et al., 2018), as well as using an IMeasureU BlueThunder device to categorise kick types in Australian rules football (Ellens et al., 2017, Cust et al., 2021).

The broad utilisation of wearable IMUs for measuring sport-specific actions likely ascribes to their relatively low expense (Burgess, 2017; O'Reilly et al., 2018; Robertson, 2020) which, as well as the obvious start-up cost of an exercise detection system (i.e., hardware, software), relates to the human resources required during the daily processes of collecting, cleaning, interpreting, and reporting the data gathered (Robertson et al., 2017). Moreover, the low invasiveness (Cardinale & Varley, 2017), time-efficiency (Gabbett, 2013; Lutz et al., 2020), and ease of implementation (Buchheit & Simpson, 2017) of wearable IMUs, compared to alternative methods such as semi-automatic multiple camera tracking systems (see Section 2.3.3.3), may be especially advantageous for EFL clubs who are less prosperous, and less well-equipped, than those in the EPL (Deloitte, 2020; Wilson et al., 2020).

#### 2.3.4.2. Validity and Reliability

To accurately interpret the data provided by wearable MEMS, it is crucial that their validity and reliability is independently examined (Scott et al., 2016b; Thorpe et al., 2017). This enables practitioners to make evidence-based decisions having distinguished the 'signal' from the TEM (i.e., 'noise') within specific variables of interest (Malone et al., 2020). Many researchers have sought to establish the validity and reliability of different MEMS devices for quantifying sport-specific movements. Considering the aforesaid applications of such technology, the remainder of this section provides examples of empirical investigations that have established these parameters.

Ahmadi and colleagues (2009), quantified the angular velocity of shoulder rotation, upper arm internal rotation, and wrist flexion during tennis by affixing three Kionix IMU devices to the corresponding anatomical sites. Using the VICON motion capture system as a criterion measure, which comprises eight cameras sampling at 100 Hz recording the position of 18 optical markers, Ahmadi et al. (2009) reported a strong correlation between the two methods (r = 0.87,  $p \le 0.001$ ), concluding that the IMU could be used with assurance for assessing the determinants of a tennis serve.

Gabbett et al. (2010) reported that the triaxial accelerometer located within MinimaxX<sup>TM</sup> S4 devices, which also sampled at 100 Hz, exhibited no statistically significant differences ( $p \ge 0.005$ ) and a strong overall correlation (r = 0.96,  $p \le 0.001$ ) between the frequency of mild ( $\overline{X}^{diff} = -1.0$ , r = 0.89), moderate ( $\overline{X}^{diff} = 4.0$ , r = 0.97), and heavy ( $\overline{X}^{diff} = -4.0$ , r = 0.99) collisions and the manually coded video footage of the 184 respective incidents observed during professional rugby league training. Collisions were detected when a spike in instantaneous PlayerLoad<sup>TM</sup> was immediately followed by the device being located in a non-vertical position. The lack of statistically significant differences, combined with the strong correlations, lead Gabbett et al. (2010), to conclude that the MinimaxX<sup>TM</sup> S4 devices provide a valid method of automatically quantifying the contact load within collision sport athletes. Additionally, Gastin et al. (2013), discovered no significant differences between the incidence of low-(n = 115), medium- (n = 218), and high-intensity (n = 19) tackles recorded by MinimaxX<sup>TM</sup> S4 devices and those manually coded during four Australian Football League matches. Whilst a specific value was not reported, Gastin et al. (2013) reported a level of ecological validity, which provided further support for the use of accelerometers to assess sport-specific collisions.

Dadashi et al. (2012) compared the efficacy of one sacrum-mounted Physilog<sup>®</sup> IMU, containing a triaxial 11 g accelerometer and 900°·s<sup>-1</sup> triaxial gyroscope sampling at 500 Hz, with a criterion 100 Hz SpeedRT<sup>®</sup> tethered system for measuring instantaneous velocity during swimming. Having measured 1,448 front crawl stroke cycles, Dadashi and colleagues (2012), reported no significant differences ( $\overline{X}^{\text{diff}} = 0.6 \pm 5.4 \text{ cm} \cdot \text{s}^{-1}$ ,  $p \ge 0.001$ ) and a strong correlation (r = 0.94,  $p \le 0.001$ ) between the two methods, leading the authors to endorse the use of IMU technology for measuring instantaneous front crawl velocity in swimming outside of the laboratory setting. Chardonnens et al. (2012), used the criterion VICON system to establish the validity and reliability of the same Physilog<sup>®</sup> IMU, affixed to the thigh and shank using custom straps, for detecting the take-off release, take-off, and early flight temporal phases of a ski jump (Schwameder, 2008). Having established the accuracy ( $\overline{X} = 9.17$  ms) and precision ( $\overline{X} = 32.33$  ms) of the IMU during 40 indoor and 36 outdoor jumps, the authors concluded that inertial sensors are capable of accurately and reliably detecting the key phases of a ski jump based on the angular velocity of a skier's knee and shank. Moreover, Harding et al. (2008) demonstrated the efficacy of the IMU components within Catapult's MinimaxX<sup>TM</sup> S4 devices, when attached to the lower back, for reliably classifying the air time and rotational angle of aerial acrobatics manoeuvres performed in elite half-pipe snowboarding ( $R^2 = 0.77$ ,  $r = 0.88 \pm 0.11$ ,  $p \le 0.001$ ).

As discussed further in Section 2.5.1, Jowitt and colleagues (2020) examined the validity of the inertial components within Catapult's OptimEye S5, which sampled at 100 Hz, for predicting fast bowling deliveries in professional cricket. Having observed a strong correlation (r = 0.95) between more than 20,000 manually recorded events and the corresponding trunk-mounted IMU data, Jowitt et al. (2020) developed a highly sensitive ( $\overline{X} = 98.0\%$ ) and specific ( $\overline{X} = 97.6\%$ ) machine learning algorithm, and subsequently concluded that MEMS represent a valid method of efficiently monitoring the workload of professional cricketers.

Wang et al. (2018) reported that a bespoke wrist-mounted IMU, with embedded machine learning algorithms (Section 2.5.1), was capable of discriminating between spike actions performed by elite and non-elite volleyball players with a high mean prediction accuracy of 94.0%. The capabilities of the IMeasureU BlueThunder device examined by Cust et al. (2021), which contained a 16 g triaxial accelerometer and  $2000^{\circ} \cdot s^{-1}$  triaxial gyroscope sampling at 500 Hz (Parrington et al., 2016), was established during four types of kicking action performed by Australian football players. Having obtained video footage of the 587 kicks performed throughout the experimental protocol, Cust et al. (2021) demonstrated that the IMU was capable of differentiating between drop punt, grubber, surge, and snap kicks with an overall accuracy of 82.8%.

### 2.3.4.3. Considerations

One limitation associated with the implementation of wearable microtechnology for measuring gross fatiguing sport-specific technical actions relates to players' adherence with this monitoring method (Burgess, 2017; Nassis, 2017). The miniaturisation of MEMS, allowing IMUs being embedded within wearable garments (Cardinale & Varley, 2017), has contributed to some players perceiving wearable microtechnology as uncomfortable (Taberner et al., 2020). Consequently, sporadic adherence with MEMS leaves practitioners with incomplete datasets, which complicates longitudinal player monitoring (Plews et al., 2014; Fullagar et al., 2019b; Borg et al., 2021). Further, the philosophy of a head coach has the potential to facilitate, or inhibit, the implementation of evidence-based player monitoring protocols in practice (Thornton et al., 2019). A non-receptive head coach (McCall et al., 2016b), with a dismissive attitude towards MEMS (Bartlett & Drust, 2020), may influence the behaviours of key stakeholders at a professional soccer club. Therefore, practitioners should understand and complement the philosophy of a head coach with regular communication, openness, and a collaborative approach across multidisciplinary departments (Gabbett et al., 2018; Malone et al., 2020).

The findings of previous research communicated throughout this section collectively demonstrate the efficacy of MEMS for measuring a multitude of sport-specific actions. It might be considered surprising, therefore, that the applicability of wearable IMUs for quantifying technical actions in soccer remains to be explored. According to the Laws of the Game (Law 4.4; IFAB, 2020), any piece of wearable microtechnology worn as part of electronic performance tracking systems must bear the FIFA International March Standard mark. This requirement came into fruition at the beginning of the 2017/2018 season, to ensure that MEMS do not endanger players in any way, as independently established by an accredited test institution (FIFA, 2020). However, of the 28 wearable devices listed in the FIFA database as authorised for use in official competition (FIFA, 2021), none are capable of measuring the frequency of soccer-specific technical actions. Therefore, practitioners are left with the difficult task of weighing up the considerations noted throughout the previous sections when deciding which, if any, method of quantifying technical performance during match-play adequately translates to the training environment.

### 2.4. Professional Soccer Training

Optimal performance with minimal injury risk is predominantly determined by the training stimuli that soccer players are exposed to (Verheul et al., 2020), with performance being the culmination of a long-term process of training intended to equip players with the necessary competencies required to excel during competition (Stølen et al., 2005; Sampaio & Maçãs, 2012). Constructing and delivering training sessions that develop these competencies is the primary role of the professional soccer coach (Williams & Reilly, 2000). The highly competitive nature of professional soccer has, therefore, compelled practitioners to adopt an increasingly evidence-based background to the structure and preparation of training programmes (Malone et al., 2015), which is to be discussed further in the next section.

Figure 2.3 depicts the plausible structure and content of a training week in which the majority of players' conditioning requirements can be sufficiently addressed. Walker and Hawkins (2018), proposed that a two-day post-competition recovery period, combined with a mid-week training stimulus (Malone et al., 2020) followed by period of specific technical and tactical preparation for an impending fixture, ensures appropriate training activities that maximise competition readiness can be administered (Anderson et al., 2016; Mujika et al., 2018). However, as mentioned in Section 1.1, the congested multicyclic in-season phase of the EFL Championship often requires players to go through a bi-weekly, and occasionally tri-weekly, round of competition, recovery, training, and subsequent competition (Issurin, 2010; Ritchie et al., 2016). With practitioners rarely afforded the luxury of time during a training week (Walker & Hawkins, 2018), and training activities often being solely determined by the head coach (Los Arcos et al., 2017), the development of technical skills and tactical strategies takes precedence over other components of the wider training programme (Morgans et al., 2014a). This is because technical and tactical parameters are closely associated with competition success (Carling, 2013). For instance, multivariate discriminant analyses have revealed that attacking-related variables (e.g., total shots, shots on target) were able to significantly differentiate between winning, drawing, and losing teams during three consecutive FIFA World Cup competitions (Castellano et al., 2012). Training programmes are most efficacious when the activities prescribed closely resemble those performed during match-play (Taylor et al., 2017). Therefore, the objective data gathered as a result of monitoring technical performance, using the multiple methods available during match-play, helps practitioners to

devise training activities that are specific to the positional demands of the respective competition (Dellal et al., 2011a; Baptista et al., 2018). This information is often difficult for head coaches to detect using their subjective perception alone (Calder & Durbach, 2015), highlighting the importance of adopting an objective approach to quantify player performance in both settings (Hughes & Franks, 2004; 2015).



**Figure 2.3:** A schematic of the plausible structure and content of a typical professional soccer training microcycle that contains only one fixture (adapted from Walker & Hawkins, 2018). **N.B.** Dashed lines represent the commencement of a new microcycle. MD = match day.

Previous research has proposed that all soccer training activities can be classified into two dichotomous categories: 'training form' or 'playing form' (Ford et al., 2010; Cushion et al., 2012). Training form activities are described as individual or small group practices performed without a matchplay context (Cushion et al., 2012), such as physical conditioning or technical drills. This differs from playing form activities, which directly relate to competitive scenarios (Ford et al., 2010) and encapsulate practices such as tactical drills and small-sided games (SSG). Given their discrete, blocked, and consistent practice conditions (Schmidt & Lee, 2005), training form activities typically promote the acquisition of technical skills (e.g., passing, crossing, shooting) in isolation, providing players with relatively few perceptual-cognitive stimuli (e.g., anticipation, decision-making) (Williams & Ford, 2008; Cushion et al., 2012). Contrastingly, the increasingly variable and distributed practices classified as playing form, which are more representative of match-play conditions, encourages the transfer of technical skills to competition (Ford et al., 2010).

Having systematically observed the practice activities employed by a sample of 25 soccer coaches, all of whom were accredited with a minimum of a UEFA 'B' License, Ford and colleagues (2010) reported that elite players spent  $60.0\% \pm 20.0\%$  of overall training time taking part in training form activities, with  $21.0\% \pm 13.0\%$  of this being technical drills. Contrary to the authors' hypotheses, the proportion of training classified as playing form did not significantly differ between elite and nonelite players ( $\overline{X}^{\text{diff}} = 9.5\%$ ,  $p \ge 0.005$ ). The findings reported by Ford et al. (2010) provided evidence to support the seminal work of Starkes (2000), later revisited by Hopwood et al. (2015), who also reported no statistically significant difference between the time spent engaging in sport-specific play (i.e., playing form) according to skill level reported by 209 athletes from 33 sports. This begins to question whether elite athletes are devoting too much time 'training to train' rather than 'training to compete' (Balyi & Haminton, 2004; Ford et al., 2011), by engaging in training form activities that are unlikely to provide sufficient perceptual-cognitive, physiological, and motor stimuli encountered during matchplay (Reilly et al., 2000; Williams & Hodges, 2005). Practitioners should encourage training to compete when appropriate, to ensure players receive training stimuli that supersede the most intense passages of play (i.e., the worst-case scenario) encountered during competition (Pollard et al., 2018; Wass et al., 2020; Malone et al., 2020).

### 2.4.1. Periodisation of Professional Soccer Training

The overall purpose of the training process in professional soccer is to administer appropriate activities that evoke suitable perceptual-cognitive, physiological, and motor stimuli (Jaspers et al., 2017) that promote adaptations, which enhance individual and team performance (Akenhead et al., 2016). It is theoretically accepted (e.g., Seyle, 1950; Impellizzeri et al., 2005), that field-based soccer training modalities must apply sufficient stressors to induce physiological adaptations, which allow players to withstand the demands of, and optimise performance during, competitive match-play (Dellal et al., 2010; McLaren et al., 2018). Such adaptive responses to training are attained as a consequence of the progressive manipulation of fundamental training variables, encompassing (but not limited to) the volume, intensity, duration, and type of exercise (Fry et al., 1992; White et al., 2020). The product of the volume and intensity of training is commonly referred to as training 'load' (Mujika et al., 2004; Manzi et al., 2010), depicted as the input variable used to induce a training outcome (Impellizzeri et al., 2020). Training load has been represented as either internal or external (Impellizzeri et al., 2004), dependent upon whether the measurable variables occur internally or externally to the player (Impellizzeri et al., 2005). External training load is generally sport-specific (Scott et al., 2016a) which, in soccer, encompasses multifaceted variables such as total distance, mean speed, and the frequency of specific technical actions performed (Wallace et al., 2014). Players' physiological responses to the same activities (i.e., internal load) may differ (Abbott et al., 2018), resulting in a variable adaptive response (Hunter et al., 2015).

The progressive manipulation of training load is commonly referred to as periodisation, which is considered as the salient planning strategy for player preparation (Impellizzeri et al., 2005; Issurin, 2016). Although countless definitions of periodisation exist throughout the literature, each with very subtle differences between authors (Mujika et al., 2018), there is general agreement that periodisation involves the methodical sequencing of different training units (i.e., long-term, medium-term, and short-term) to systematically control the adaptive response to training (Gambetta, 2004; Lambert et al., 2008; Issurin, 2010). In the context of professional soccer, these main structural components of a training programme are typically known as a macrocycle (i.e., the duration of the season), mesocycle (i.e., a multi-week training block), and microcycle (i.e., each training week) (Matveyev, 1981; Norris & Smith,

2002). Rather than a rigid concept, Norris and Smith (2002) considered periodisation as a directional framework, within which training programmes can be tailored to the specific requirements of each athlete. As well as the traditional manipulation of athletes' external training load (Todd et al., 2012), the flexible nature of contemporary periodisation has enabled the sequential integration of multiple components (Bompa, 1999). That is, the integrated periodisation of recovery practices, nutritional strategies, psychological components, and skill acquisition may contribute to optimal performance during competition (Mujika et al., 2018). However, the integration of skill-related performance parameters within a comprehensive periodisation plan has received comparably less scholarly attention than the four formerly mentioned components, contributing to a scarcity of empirical evidence surrounding this topic.

## 2.4.1.1. Periodisation of External Training Load

When planning a training programme, practitioners must not only recognise specific technical and tactical objectives, but also the positive and negative implications, of each individual training session and the net result of the accrued training load when a fixture takes place (Akenhead et al., 2016). For outfield players who complete a full match, MD generally represents the most demanding day of each microcycle (Anderson et al., 2015). Consequently, within-microcycle periodisation strategies are often arranged with the aim of maximising recovery and minimising residual neuromuscular fatigue prior to competition (Vanrenterghem et al., 2017; Hills et al., 2020b).

Previous research has explored the periodisation practices employed by practitioners to prepare professional soccer players for the multidimensional demands of competition. Much of the available literature has been conducted during the in-season phase, examining short one-week microcycles (Anderson et al., 2015; Malone et al., 2015; Stevens et al., 2017; Martín-García et al., 2018), mesocycles from four-to-10 weeks (Scott et al., 2013; Abade et al., 2014; Gaudino et al., 2014) and lengthier training blocks of three-to-four months (Alexiou & Coutts, 2008; Casamichana et al., 2013). As well as these insights into the in-season phase, Manzi et al. (2013) examined training load during the pre-season preparatory period, whilst Jeong et al. (2011), compared training practices during pre-season with inseason.

When investigating specific in-season microcycles, practitioners have generally adopted the standardised method of categorising individual training sessions in relation to the number of days prior to a competitive fixture that they take place (i.e., MD minus day number [MD - n]) (Malone et al., 2015). Subsequently, researchers that have quantified the within-microcycle periodisation strategies have consistently demonstrated that markers of external training load (e.g., total distance, mean speed) are at their lowest on the day immediately before competition. For instance, Stevens et al. (2017) examined the within-microcycle differences in the external training load encountered by Dutch Eredivisie players, reporting that total distance exhibited progressive reductions as competition approached. Specifically, Stevens and colleagues (2017) reported MD - 1 values ( $\overline{X} = 3,848.0 \pm 454.0$ m) significantly lower than that observed on MD - 4 ( $\overline{X}^{\text{diff}}$  = 3,419.0 ± 459.0 m,  $p \le 0.005$ ), MD - 3 ( $\overline{X}^{\text{diff}}$ = 2,272.0 ± 734.0 m,  $p \le 0.005$ ) and MD - 2 ( $\overline{X}^{diff}$  = 1,371.0 ± 427.0 m,  $p \le 0.005$ ), respectively. In a similar investigation conducted within Spanish Primera División players, Martín-García et al. (2018) reported that total distance exhibited progressive declines as competition neared (ES = 1.2 - 3.1, largeto-very large), with MD - 1 values ( $\overline{X} = 2,657.3 \pm 601.7$  m) being significantly lower than MD - 4 ( $\overline{X}^{\text{diff}}$ = 2,447.9 ± 302.8 m,  $p \le 0.005$ ), MD - 3 ( $\overline{X}^{diff}$  = 2,927.5 ± 604.0 m,  $p \le 0.005$ ) and MD - 2 ( $\overline{X}^{diff}$  =  $1,545.3 \pm 18.5$  m,  $p \le 0.005$ ). Together, these studies demonstrate that practitioners may adopt a tapering approach to their within-microcycle training prescription, in an attempt to physically unload players and increase readiness for an impending fixture (Malone et al., 2015; Owen et al., 2017). Anecdotally, this unloading coincides with training activities becoming more technically and tactically oriented (Martín-García et al, 2018; Walker & Hawkins, 2018). Yet, for reasons aforementioned in Section 2.3, empirical evidence that demonstrates this is lacking.

Another similarity throughout the literature that has explored periodisation practices during professional soccer training microcycles is that the external load experienced by players tends to peak on the fourth day preceding a fixture. Stevens et al. (2017), reported significantly higher total distance values on MD - 4 ( $\overline{X}$  = 7,267.0 ± 913.0 m) than MD - 3 ( $\overline{X}^{\text{diff}}$  = 1,147.0 ± 275.0 m,  $p \le 0.005$ ), MD - 2 ( $\overline{X}^{\text{diff}}$  = 2,048.0 ± 32.0 m,  $p \le 0.005$ ) and MD - 1 ( $\overline{X}^{\text{diff}}$  = 3,419.0 ± 459.0 m,  $p \le 0.005$ ). Furthermore, Martín-García et al. (2018) recorded significantly greater high-speed running distance (> 19.8 km·h<sup>-1</sup>)

values on MD - 4 ( $\overline{X}$  = 245.6 ± 148.6 m) than MD - 2 ( $\overline{X}^{diff}$  = 158.3 ± 74.7 m,  $p \le 0.005$ ) and MD - 1 ( $\overline{X}^{diff}$  = 195.7 ± 91.7 m,  $p \le 0.005$ ). Referring back to the structure of a single-game microcycle illustrated by Figure 2.3, the trend for professional soccer players to exhibit the highest external training load on MD - 4 likely relates to training content delivered on this day (Scott et al., 2013). That is, with no midweek fixture, practitioners are more likely to deliver both 'intensive' and 'extensive' soccer activities during the mid-week training phase. Intensive soccer emphasises components of performance such as players' acceleration, deceleration and change of direction ability. This differs from extensive soccer activities, which utilise larger areas to mimic actual match-play (Walker & Hawkins, 2018; Malone et al., 2020).

## 2.4.2. Professional Soccer Training Drills

Head coaches play an important role in the systematic manipulation of players' training load. Whilst practitioners may possess a varying degree of influence concerning the activities performed during a training microcycle (Weston, 2018), the head coach generally dictates the day-to-day selection of which drills are included in specific training sessions, based on the perceived technical and tactical needs of their squad (Anderson et al., 2016; Los Arcos et al., 2017). Despite practitioners employing a variety of training drills to maximise their contact time with players by concurrently developing multiple performance components (Dellal et al., 2012; Barrett et al., 2020), club confidentiality policies may explain the scarcity of academic understanding regarding the specific training drills performed by players during a typical weekly microcycle.

Much of the available literature examining soccer training drills has focussed solely on SSG. These are a popular training modality employed by practitioners, thought to maximise training efficiency by simultaneously developing players' technical, tactical, physiological, and psychological components of performance (Fradua et al., 2013; Aguiar et al., 2015). Such drills are easily modifiable, with an abundance of literature determining the influence of pitch dimensions (Kelly & Drust, 2009; Casamichana & Castellano, 2010; Hodgson et al., 2014), number of players (Katis & Kellis, 2009; Owen et al., 2011; Brandes et al., 2012; Dellal et al., 2012; Aguiar et al., 2013; 2015), technical rules (Hill-Haas et al., 2010; Dellal et al., 2011b; Abrantes et al., 2012; Ngo et al., 2012), the inclusion of goalkeepers (Castellano et al., 2013; Casamichana & Castellano, 2015; Hulka et al., 2016), and game duration (Köklü et al., 2012; 2017) on multifarious indices of performance. This body of research demonstrates the importance of training session design in modulating the nature and magnitude of the training stimuli that players are exposed to (Barrett et al., 2020).

Until last year, the types of training drill executed by professional soccer players had not been objectively reported. However, having collected a dataset comprising 65,825 individual drill observations from one club from each of EPL, EFL Championship and EFL League One over an 8-season period, Barrett and colleagues (2020) (in conjunction with eight head coaches) assigned each observation into one of six distinct categories (Table 4.1). Notwithstanding the substantial variation between the eight head coaches, attributed to their respective philosophies (Hughes et al., 2012; Wright et al., 2012; 2013), SSG were the most frequently performed training modality (n = 21,722, 33.0%), followed by possession (n = 17,773, 27.0%), technical (n = 9,874, 15.0%), and tactical (n = 7,241, 11.0%) drills. Drills classified as conditioning (n = 6,583, 10.0%) and position specific (n = 2,633, 4.0%) were the two training modalities which featured the least throughout the eight-season period (Barrett et al., 2020).

As well as quantifying the composition of training sessions, Barrett et al. (2020) established the effect of drill category on seven indices of external training load, highlighting trivial-to-very large (ES = 0.02 - 2.70) between-drill differences in players' absolute and relative total distance, relative PlayerLoad<sup>TM</sup>, and the relative frequency of high-intensity acceleration/deceleration efforts. Moreover, between-drill inter-positional differences were apparent within all variables with the exception of relative sprint distance, with CM exhibiting significantly greater absolute total distance values than ST (p = 0.012, ES = 0.15, trivial) and WD ( $p \le 0.001$ , ES = 0.19, trivial) during a typical drill (Barrett et al., 2020). Due to this contemporary investigation being the first to establish the incidence, and associated physical outputs, of different types of training drill executed by professional soccer players, a parallel examination of the frequency of technical actions elicited by each drill is currently absent from the literature. With soccer-specific technical actions being an important, yet commonly overlooked (Paul et al., 2015; Malone et al., 2020), component of external training load (Wallace et al.,

2014; Scott et al., 2016a), such an investigation may assist head coaches in the prescription of drills to satisfy pre-determined training objectives (Jaspers et al., 2017).

### 2.4.3. Periodisation of Technical Actions

Previous research concerning the acquisition of sport-specific motor skills has typically focused upon singular constructs, such as practice organisation (i.e., blocked vs random, constant vs variable, massed vs distributed), method of instruction (i.e., internal vs external, simple vs complex), or the timing and nature of feedback (i.e., delayed vs immediate, knowledge of performance vs knowledge of results) (Hodges & Williams, 2012; Farrow et al., 2013; Magill & Anderson, 2017). Unlike the physical training literature, the periodisation of skill-related performance in professional soccer has experienced little attention (Farrow & Robertson, 2017; Mujika et al., 2018). Whilst applied models have been proposed that provide some guidance regarding progressive skill acquisition techniques (Vickers et al., 1999; Carson & Collins, 2011), and the optimisation of training environments to provide a sufficient challenge point that promotes athletic mastery (Ericsson et al., 1993; Guadagnoli & Lee, 2004), there has been only one attempt to combine numerous constructs into one framework (Mujika et al., 2018). Farrow and Robertson (2017) labelled this as the skill acquisition periodisation framework, which adapts prominent principles that feature heavily throughout the physical training literature into a model for systematically manipulating sport-specific technical performance. The principles of specificity, progression, overload, reversibility, and tedium (commonly referred to as S. P. O. R. T.) (Grout & Long, 2009), have been re-conceptualised and applied to the relevant principles of skill acquisition, resulting in a holistic framework enabling practitioners to monitor technical actions both acutely and longitudinally (Farrow & Robertson, 2017). Using soccer training as an applied example, the remainder of this section illustrates how each of these principles has translated from the physical training domain to become applicable to players' technical performance.

## Specificity

The notion of specificity relates to the extent to which training regimes mimic the technical demands of competition (Pinder et al., 2011). Theoretically, practitioners should design and deliver training drills

that are representative of the individual, environmental, and task constraints experienced during matchplay (Araújo et al., 2006; Davids, 2008). For instance, as opposed to ST practicing their finishing in a static manner, with few environmental cues, practitioners should devise dynamic finishing drills that more closely replicate the perceptual-cognitive stimuli, and lower-limb coordination patterns, encountered during competition (Wilson et al., 2008; Harrop & Nevill, 2014).

## Progression

In the context of skill acquisition, the principle of progression can be expressed in two ways. Of course, measurable improvements in players' skill-related performance are, arguably, the overriding benchmark. However, Farrow and Robertson (2017) depict progression as a player's capacity to endure a heightened 'technical load', considered as the increased frequency of technical action repetitions. Although the role of meticulous training in becoming an expert performer has been questioned (Hambrick et al., 2014), the authors present this principle in relation to the established theory of deliberate practice (Ericsson et al., 1993), which suggests that players striving for athletic mastery must seek training scenarios involving a goal, which exceeds their current level of performance (i.e., training to compete) (Ford et al., 2011; Farrow & Robertson, 2017). With reference to the previously discussed example, practitioners may design dynamic finishing drills that incrementally increase the frequency and/or complexity of practice repetitions to ensure each player is optimally challenged (Guadagnoli & Lee, 2004).

# Overload

The principle of overload is closely associated with progression, with both constructs being pertinent in ensuring a training programme is coherently periodised (Mujika et al., 2018). From a physical perspective, a progressive increase in players' external training load is needed to enhance the body's capacity to do work (Bompa, 1994). With reference to technical performance, Farrow and Robertson (2017) likened overload to the degree of cognitive exertion required during a given task, somewhat comparable to internal training load (Abbott et al., 2018). Described as the mental work involved during decision-making processes (Marcora et al., 2009), cognitive exertion plays a fundamental role during

skill-related performance in soccer. In such a complicated environment, professional players must process vast amounts of information to permit accurate decisions to be made rapidly (Araújo et al., 2006; Barreiros et al., 2007). To facilitate the principle of overload, practitioners may restrict the time available for ST to complete the prior dynamic finishing drill, whilst pressuring the player to score as many goals as possible. This restriction may be gradually increased over time, with players' response to this overload gauged through monitoring performance-related metrics (e.g., shots on target, goals scored), alongside players' self-reported cognitive exertion (Impellizzeri et al., 2004; McLaren et al., 2017).

## Reversibility

Reversibility precepts that players may forgo the favourable effects of training when such activities substantially fluctuate, diminish, or discontinue, leading to a decline in performance (Colby et al., 2018; Buckthorpe et al., 2019). This principle highlights the importance of players' technical performance being consistently quantified, allowing practitioners to determine the degree of skill learning that was accomplished over a period of time and, crucially, how permanent (or reversible) this learning was (Mujika et al., 2018). By delivering the same dynamic finishing drill, following a period of discontinued activity, practitioners are able to enact retention testing to determine whether any previously attained performance enhancements have reversed (Magill & Anderson, 2017). Establishing how long a specific technical action can be left before the effects of reversibility take hold may be useful for practitioners (Mujika et al., 2018), especially during the in-season period, with limited training time meaning that specific components of training (e.g., tactical preparation) must be prioritised according to a team's competition schedule (Scott et al., 2013).

#### Tedium

The final principle of the skill acquisition periodisation framework refers to the notion of tedium: a detrimental state of boredom owing to monotonous training practices (Farrow & Robertson, 2017). Through the intentional alteration of one or more variables (Kraemer & Ratamess, 2004), practitioners can prevent training becoming monotonous and, subsequently, promote 'repetition without repetition'

(Bernstein, 1967). This remark summarises Bernstein's (1967) theory of motor skill learning, which suggested that, due to movement being inherently complex and variable by nature, two movement patterns will never be exactly the same. However, there are examples of skill-related training in sport that contradict Bernstein's proposition, such as electronic guidance devices being frequently used in golf to constrain a particular swing and refine desired movement patterns (Glazier, 2010). Notwithstanding, Farrow and Robertson (2017) advocate practitioners applying a continuum of variety during training, involving a fluctuating degree of cognitive exertion, as opposed to players passively enacting pre-determined movement patterns (Brady, 1998). Referring to the previous example of a dynamic finishing drill, practitioners can prevent tedium and promote practice variability by systematically altering factors such as players' ball approach (i.e., stationary, walk, run, skip), restricting the space available to shoot towards the goal, the density of players around the ST, or the inclusion/exclusion of goalkeepers (Farrow & Robertson, 2017). Theoretically, these alterations encourage exploration and appreciation of the stability of a specific skill (Savelsbergh et al., 2010), contributing to technical performance enhancements (Mujika et al., 2018).

Prescribing soccer players with training activities that consistently adhere to the principles of skill acquisition periodisation should contribute towards sustained improvements to skill-related performance. Yet, longitudinal compliance with this framework requires players' technical actions to be routinely objectified. The infeasibility of currently available measurement methods to be implemented in the training environment, for reasons discussed throughout Section 2.3, has led practitioners to seek alternative means for quantifying technical actions during professional soccer training. Therefore, the following section shall discuss the prospect of utilising automotive wearable microtechnology to solve the problems currently encountered in practice.

## 2.5. Foot-Mounted Inertial Measurement Units

The majority of commercially available MEMS devices are situated between players' scapulae, housed in tightly fitting neoprene garments to minimise movement artefacts (Figure 2.4) (Varley et al., 2017). However, given the questionable ability of trunk-mounted devices to detect discrete segmental movements (Edwards et al., 2019), the attachment site during body-worn accelerometery is of critical concern (Nedergaard et al., 2017; Vanrenterghem et al., 2017). As mentioned in Section 2.3.4, the everdecreasing size, cost, and power consumption of IMUs has encouraged practitioners to explore alternative anatomical locations to placing these devices in the thoracic region (Mannini & Sabatani, 2010; Barrett et al., 2014). Within gait tracking and the recognition of sport-specific activities, researchers have explored the possibility of locating IMUs at athletes' lower limbs (Zhou et al., 2016). This attachment site may be especially relevant in professional soccer as, of course, the vast majority of technical actions performed during soccer are performed in this region.



**Figure 2.4:** The anatomical location of a Catapult MinimaxX<sup>TM</sup> S4 MEMS device, which integrates GPS and IMU components, situated between the scapulae in a tightly fitting neoprene garment (adapted from Langsdon, 2015).

## 2.5.1. Machine Learning and Artificial Intelligence

To reduce human error and manual data processing limitations, practitioners working in professional sport are increasingly using machine learning and artificial intelligence methods to automate decision-making processes (Lapham & Bartlett, 1995; Ward et al., 2019). Machine learning is a method that

develops computerised systems to automatically improve with more data (Ofoghi et al., 2013), with algorithms representing the statistical operations involved during automated movement recognition (Shalev-Shwartz & Ben-David, 2014; LeCun et al., 2015).

Machine learning approaches are commonly used for recognising sport-specific activities using MEMS (Kelly et al., 2012; Cust et al., 2019). Aforesaid examples (see Section 2.3.4.1) include Wang et al. (2018), who utilised wrist-mounted IMUs to monitor spike actions performed by elite and nonelite volleyball players, and Jowitt et al. (2020), who developed and 'trained' an automatic fast bowling detection algorithm using professional cricketers.

Cust et al. (2021) used ankle-mounted IMUs to monitor kicking in Australian rules football training. As depicted below (Figure 2.5), Cust and colleagues (2021) evaluated the efficacy of the machine learning algorithms within these IMUs by following the traditional parametric statistical technique of calculating the device's 'precision' and 'recall' (Forman & Scholz, 2010; Géron, 2019). In this context, the precision of the device refers to the proportion of total reported kicks that actually occurred, with recall being the proportion of total kicks that were successfully detected. The method of calculating precision and recall yields values that are between 0.0 and 1.0, with 1.0 representing an algorithm that can differentiate between positive and negative cases perfectly (Fawcett, 2006; Pedregosa et al., 2011).



**Figure 2.5:** A schematic of a confusion matrix, with corresponding equations, used to determine the efficacy of machine learning algorithms for detecting sport-specific movements (adapted from Ma et al., 2019).

A newly commercially available foot-mounted IMU (PlayerMaker<sup>™</sup>), measures the frequency of soccer-specific technical actions using an amalgamation of machine learning algorithms and artificial intelligence techniques. However, the ability for conventional machine learning algorithms to process raw accelerometer and gyroscope traces is limited (Kautz, 2017), with specific data processing stages required to produce usable data (Figo et al., 2010). Therefore, to detect these actions, the orientation, velocity, and position vectors of soccer players' feet are determined through these raw traces being transformed using Butterworth and Kalman filters within the IMU's microprocessor (Figure 2.6; Waldron et al., 2020). This enables the foot-mounted IMUs to measure technical actions in an automated fashion, with the potential to replace laborious manual coding with this contemporary machine learning-based approach (Doshi-Velez & Kim, 2017; Halilaj et al., 2018).



**Figure 2.6:** A schematic of the data processing procedures that take place within the PlayerMaker<sup>™</sup> foot-mounted IMU (adapted from Waldron et al., 2020).

# 2.5.2. Applications of Foot-Mounted Inertial Measurement Units

Wearable accelerometers and gyroscopes provide practitioners with a non-invasive method of measuring the frequency and intensity of sport-specific events that may be difficult for head coaches to subjectively pinpoint (Castellano et al., 2012; Chambers et al., 2015; Walker et al., 2016). However, the utility of foot-mounted IMUs for monitoring professional soccer player performance is yet to be fully explored (Waldron et al., 2020). By combining proprietary gait tracking with soccer-specific event detection algorithms, the PlayerMaker<sup>TM</sup> foot-mounted IMU is an example of wearable microtechnology that measures the frequency and intensity of sport-specific technical actions performed during soccer (Figure 2.7). The PlayerMaker<sup>TM</sup> device, which samples at 1000 Hz, incorporates two components from the MPU-9150 (InvenSense, California, USA) nine-axis multi-chip motion tracking module (Waldron et al., 2020), being a 16 g triaxial piezoelectric accelerometer and a 2000° s<sup>-1</sup> triaxial piezoelectric gyroscope.



**Figure 2.7:** One PlayerMaker<sup>™</sup> foot-mounted IMU, encased within a manufacturer supplied silicone strap, affixed to the left lateral malleolus over a studded soccer boot (PlayerMaker<sup>™</sup>, 2021).

Triaxial accelerometers are highly sensitive three-dimensional motion sensors that measure a composite vector magnitude, expressed as gravitational force (Cummins et al., 2013), by quantifying the frequency and magnitude of accelerations in the anterior-posterior, mediolateral, and longitudinal direction (i.e., the X, Y, and Z planes) (Boyd et al., 2011; Barrett et al., 2016). Triaxial gyroscopes measure angular motion (Gabbett, 2013), by quantifying the frequency and velocity of rotational movements which, when affixed to a joint, facilitate the evaluation of the angular velocity of a body/limb (Lutz et al., 2020). Theoretically, these IMU components should possess the capacity to identify a particular pattern within raw accelerometer and gyroscope traces that represents a soccer kick (Luinge & Vetlink, 2005; Ellens et al., 2017). The high sampling rate of IMUs (Waldron et al., 2011), combined with the ability to monitor multiple players in the absence of a satellite connection (Malone et al., 2017), represent advantages of utilising wearable IMUs in professional soccer to quickly evaluate performance and inform training prescription (Malone et al., 2017).

Professional soccer players tend to have a dominant limb for executing technical actions (Carey et al., 2001; Van Melick et al., 2017; Verbeek et al., 2017). Previous laboratory-based research, which utilised cinematography-related motion analysis techniques, has uncovered three-dimensional

kinematic differences between players' dominant and non-dominant limbs during kicking (Barfield et al., 2002; Dörge et al., 2002; Sinclair et al., 2014), which carries potential implications for their susceptibility to injury. For instance, Brophy et al. (2010), reported that male soccer players sustained a significantly greater incidence of non-contact anterior cruciate ligament injuries in their dominant limb than their non-dominant limb (%diff = 25.9,  $p \le 0.005$ ), with Svensson et al. (2018) noting significant differences in the cumulative length, width, depth, and cross-sectional area of structural hamstring injuries sustained to the dominant limb compared with the non-dominant limb ( $\vec{X}^{diff} = 1.5$  cm<sup>3</sup>, p = 0.04). These differences may be the result of significant muscular strength imbalances (Rahnama et al., 2005), and inter-segmental coordination discrepancies (Dörge et al., 2002; Apriantono et al., 2006), between the two limbs. Therefore, having an IMU situated in this region that is capable of measuring the angular velocity of the shank during kicking may help practitioners to design procedures that seek to reduce these asymmetries (Chambers et al., 2015; Verheul et al., 2020) and, subsequently, reduce injury risk and enhance player performance (Ferraz et al., 2012; Guilherme et al., 2015).

### 2.6. Summary

This review of literature has highlighted the need for professional soccer players to possess sufficient skill-related performance proficiency in order to tolerate the increasing frequency of technical actions interspersed throughout the multifactorial demands of match-play. Having determined the heightened technical demands of contemporary professional soccer through a series of published performance profiles (Section 2.2), available due to the copious methods of measuring the frequency of technical actions performed during match-play (Section 2.3), practitioners are able to tailor training activities to the specific technical requirements of each playing position. Indeed, practitioners are able to utilise a distinct skill-acquisition periodisation framework (Section 2.4.3), which translates traditional principles of physical periodisation into a structure for methodically prescribing technical actions throughout a training programme. However, in the training environment, technical actions are frequently disregarded during player monitoring processes due to measurement methods being unavailable, unfeasible, or labour intensive (Section 2.3).

The utility of wearable microtechnology, in the form of IMUs attached to players' feet, may represent a time-efficient and cost-effective alternative method allowing practitioners to automatically quantify the frequency of technical actions performed during training (Section 2.5). Such technology would facilitate the creation of a novel technical performance profile, which quantifies the withinmicrocycle, inter-positional, and between-drill differences in the frequency of technical actions executed during professional soccer training. Along with an understanding of the validity and reliability of this novel player monitoring method, such a profile would provide key stakeholders with a valuable insight into the multidimensional nature of the external training load that players must regularly contend with. Therefore, the specific aims of following experimental chapters, by which the overall purpose of this research project (Section 1.1) will be fulfilled, are:

- to establish the concurrent validity and intra-unit reliability of a foot-mounted IMU for measuring the frequency of technical actions performed during soccr training activities,
- to quantify the within-microcycle, inter-positional, and between-drill differences in the frequency of technical actions performed during professional soccer training using footmounted IMU.
# Chapter 3:

# The Concurrent Validity and Intra-Unit Reliability of Foot-Mounted Inertial Measurement Units for Quantifying Technical Actions in Soccer

#### **3.1. Introduction**

Professional soccer players no longer depend upon individual coaches to enhance their performance (Eisenmann, 2017). It is now commonplace for professional soccer clubs to employ abundant multidisciplinary practitioners (Rothwell et al., 2020), who occupy diverse roles, to provide a specialised service to their athletes (Halson et al., 2019). The discipline of performance analysis plays an imperative role during the coaching process (Groom et al., 2011; Hughes et al., 2012), with the role of the performance analyst (Wright et al., 2013) and player engagement with performance analysis (Wright et al., 2016) observing an increase in scholarly examination (Coutts, 2014b; Sarmento et al., 2014).

Coaches work meticulously with their performance analyst(s) to strategically prepare for competition through a training provision supplemented by objective data (Wright et al. 2012; Bateman & Jones, 2019). Technical performance indicators (e.g., ball touches, releases) are superior predictors of team success in comparison with time-motion performance indicators (e.g., high-intensity running distance) (Castellano et al., 2012; Carling, 2013). However, previous research (Castellano et al., 2014; Yi et al., 2020), has demonstrated that quantifying technical performance in a valid and reliable manner requires expensive semi-automatic multiple camera tracking systems (e.g., ProZone<sup>®</sup>, K = 0.99, Bradley et al., 2007) or third-party data providers (e.g., OPTA Sports, K = 0.94, Liu et al., 2013). As discussed in Section 2.3, these solutions may not be feasible for EFL soccer clubs, whose training facilities are seldom equipped with such advanced technology (Akenhead & Nassis, 2016), leaving onerous manual data collection through computerised analysis software as the primary method of quantifying technical performance away from modern stadia. However, O'Donoghue (2007) questioned the ability of manual system operators to collect objective data in a way that is consistently valid and reliable, contributing to a paucity of research examining technical performance during professional soccer training.

A potential solution to this problem is through the use of wearable microtechnology (Section 2.3.4). The widespread application of wearables has enabled practitioners to better understand the multifaceted determinants of soccer player performance (Cummins et al., 2013; Weaving et al., 2019). Devices incorporating GPS and IMUs represent the most frequently used microtechnology in professional soccer (Weston, 2018; Salter et al., 2021), providing practitioners with a plethora of data

relating to players' locomotor performance (Akenhead & Nassis, 2016). However, given that optimal competition preparation integrates technical, tactical, physiological, and psychological components (Stølen et al., 2005), and that technical and tactical elements are often prioritised during training sessions (Morgans et al., 2014a), it is surprising that practitioners regularly consider the data provided by GPS in isolation (Dalton-Barron et al., 2020; Malone et al., 2020). The integration of technical parameters would assist practitioners in their understanding of fluctuations in time-motion data in and out of possession (Paul et al., 2015), enhancing the prescription of technical conditioning drills intended to prepare players for the worst-case (Bradley & Ade, 2018) or most common scenarios.

Although practitioners have utilised wearable IMUs for many years (O'Reilly et al., 2018), the majority (if not all) of these commercially available devices are located in the thoracic region (Barrett et al., 2014). Given the questionable ability of trunk-mounted devices to detect discrete segmental movements (Edwards et al., 2019), the attachment site during body-worn accelerometery is of critical concern (Nedergaard et al., 2017). As such, a commercially available foot-mounted IMU would represent a time-efficient and cost-effective logical solution for quantifying technical actions in soccer. This may be particularly useful in the applied environment (Chambers et al., 2015), given the bilateral kinematic asymmetries that exist between players' dominant and non-dominant limbs during kicking (Dörge et al., 2002; Nunome et al., 2006; Sinclair et al., 2014). However, integral to the interpretation of the data collected by IMUs is an examination of their validity and reliability (Scott et al., 2016b). This information would allow practitioners to differentiate the signal from the noise within an IMU, thereby avoiding making crucial evidence-based decisions based upon potentially erroneous data (Malone et al., 2020). Accordingly, the aim of the current study was to establish the concurrent validity and intra-unit reliability of a foot-mounted IMU for measuring ball touches and releases during soccer training activities.

# 3.2. Methods

#### 3.2.1. Participants

Twelve male amateur soccer players (mean  $\pm$  SD age: 23.8  $\pm$  5.2 years; stature: 179.9  $\pm$  5.3 cm; mass: 85.1  $\pm$  19.5 kg) voluntarily participated in this study. Each player answered the following question,

found to accurately determine leg dominance during bilateral mobilising tasks, prior to data collection: "if you would shoot a ball on target, which leg would you use?" (Van Melick et al., 2017, p. 6). As a result, nine players described themselves as right-footed, with the remaining three being left-footed. Players were required to possess at least six years of soccer playing experience, to a minimum of regional level, thought to provide sufficient kicking accuracy with both the dominant and non-dominant feet (Nagasawa et al., 2011). As such, the players in the current study had a mean playing experience of  $16.4 \pm 5.9$  years. Institutional ethical approval (FHS200) was obtained prior to the commencement of the study, with players providing written informed consent.

#### 3.2.2. Inertial Measurement Units

The foot-mounted IMU (PlayerMaker<sup>TM</sup>, Tel Aviv, Israel) incorporated two components from the MPU-9150 multi-chip motion tracking module (InvenSense, California, USA), being a 16 g triaxial piezoelectric accelerometer and a  $2000^{\circ} \cdot s^{-1}$  triaxial piezoelectric gyroscope. The IMU sampled at a rate of 1000 Hz, with data filtered using machine learning algorithms at 250 Hz (Figure 2.6). Housed in tightly fitting silicone straps, the IMUs were bilaterally located at the lateral malleoli over the players' boots (Figure 2.7). As per manufacturer guidelines, the IMUs were activated five minutes prior to data collection to allow the acquisition of sufficient Bluetooth<sup>®</sup> signal.

# 3.2.3. Experimental Design

#### 3.2.3.1. Pilot Testing

The original experimental protocol required each player to wear one foot-mounted IMU on top of another, resulting in two devices being concurrently worn on each foot. Despite being contrary to manufacturer guidelines, this was considered a safe and appropriate method of quantifying inter-unit reliability. However, wearing two IMUs on each foot contributed to unexpected error within the raw data, with proportion of agreement ( $P_A$ ) values between 25.1% - 25.8% preventing further analyses. This was attributed to the friction between the two overlaid devices causing irregularities within the accelerometer and gyroscope traces. Moreover, the anatomical location of the superior device was approximately 12 mm higher than the inferior device, which may have interfered with the machine

learning algorithms responsible for filtering the raw data (Figure 2.6). Therefore, to remove the potential for any controllable error, the final protocol required each player to wear one IMU per foot, as per manufacturer guidelines.

# 3.2.3.2. Research Design

This study employed a repeated measures design with four conditions, completed in the stated alphabetical order (Table 3.1). For all conditions, one player served the ball to the other from each given distance. In response to each ball served, the experimental protocol required players to execute a series of rudimentary open skill soccer tasks (Singer, 2000). Although these basic tasks involved little perceptual-cognitive proficiency (Williams, 2000), players were required to respond to a predictable incoming ball from their partner. This was stipulated to diminish, as much as possible, the potential for human error impacting the data. Players executed tasks with their dominant and non-dominant feet, to facilitate comparison of the validity and reliability of the IMUs under both conditions. Each condition required players to perform 20 release repetitions, recommended to provide sufficient statistical power for reliability analyses on triaxial accelerometer data (Atkinson & Nevill, 1998). The frequency of technical actions performed collectively throughout the four conditions surpassed the typical technical performance demands of professional soccer match-play, with UEFA Champions League players typically performing  $60.2 \pm 20.7$  ball touches and  $50.1 \pm 25.7$  releases per match (Table 2.4) (Yi et al., 2020).

Condition	Task Description
А	Players were required to perform one release, without taking any additional ball touches, with their dominant foot.
В	Players were required to perform one release, without taking any additional ball touches, with their non-dominant foot.
С	Players were required to perform one ball touch, followed by one release, with their dominant foot.
D	Players were required to perform one ball touch, followed by one release, with their non- dominant foot.

Table 3.1: A description of each technical soccer task stipulated during the experimental protocol.

# **3.2.3.3.** Experimental Protocol

Prior to data collection, each player completed a standardised warm-up consisting of five minutes of low-intensity exercise on a cycle ergometer (M3i Lite, Keiser, Tetbury, UK), followed by a technical warm-up requiring five repetitions of each experimental condition. Firstly, three repetitions of each trial (360 ball touches and 240 releases in total) were performed with the players situated 13.2 m apart, with this being the mean distance progressed per possession sequence during match-play throughout the four aforementioned European competitions (see Section 2.2) (OPTA Sports, 2020). Following this, a further three repetitions of each trial were performed with 18.7 m between players, equivalent to the mean pass distance during match-play within the same competitions (OPTA Sports, 2020). The validity and reliability of technical data provided by OPTA Sports has been previously established (see Section 2.3.2.2) (Liu et al., 2013), allowing the platform to be used with assurance during academic research. Multiple soccer balls were positioned around the perimeter of the experimental protocol in case of misplaced releases. If such incidents occurred, one player was instructed to collect a new ball using only their hands to avoid interference with the IMU whilst data collection was in progress.

To minimise experimental bias, all technical actions were performed using the same FIFA approved type of soccer ball (Delta EFL, Mitre, London, UK), inflated to the manufacturer recommended pressure (42.0 - 56.0 kPa). In addition, specific foot-mounted IMUs (PlayerMaker<sup>TM</sup>, Tel

Aviv, Israel) were consistently used throughout all trials. Moreover, the same digital measuring wheel (250282, Silverline, Yeovil, UK), calibrated to 0.1 m, was used to measure the required distances, with the same 20 m x 20 m area of a daily-maintained natural grass training pitch being used throughout the protocol. Although the environmental conditions (e.g., wind speed, precipitation, humidity) were not empirically measured, the experimental protocol only took place when the researcher subjectively deemed such conditions as consistent (i.e., no rain, no gusty winds).

## 3.2.4. Video Analysis

To permit comparative analyses, each trial was captured using a fixed video camera (HDR-PJ420, Sony, Tokyo, Japan), mounted on a telescopic tripod (EF-61, Velbon, Yamanashi, Japan), situated perpendicular to the playing area at a height of 5.2 m to provide a wide angle. The footage of each trial was analysed (SportsCode Elite, v. 11.2.23, SportsTec, Warriewood, Australia), using pre-determined unequivocal operational definitions (Table 3.2) (O'Donoghue, 2007), facilitating the verification of the *in situ* monitoring of each ball touch and release performed during the protocol. Intra-operator reliability of the reference performance analyst, who conducted all analyses, was established by coding three randomly selected repetitions of each soccer task three times ( $P_A = 100.0\%$ ; Cooper et al., 2007), providing affirmation of the use of manual coding as the criterion measure in this study (O'Donoghue, 2007).

**Table 3.2:** The operational definitions of several variables used during the design and execution of the experimental protocol (adapted from PlayerMaker<sup>™</sup>, 2017; OPTA Sports, 2018).

Variable	<b>Operational Definition</b>
Ball Touch	Any instance in which the soccer ball makes contact with the foot.
Release	Any instance whereby the ball is struck by the foot, encompassing all passes, crosses, shots, and clearances.
Possession Sequence	A passage of play in which one team maintains possession of the ball, ended by defensive actions, stoppages, or a shot towards goal.
Distance Progressed per Possession Sequence	The distance that the ball has advanced towards the oppositional goal line during a possession sequence.
Successful Pass	Any release that is received by a player of the same team.
Pass Distance	The distance between two players of the same team, between whom a successful pass is executed.

#### 3.2.5. Statistical Analysis

Upon visual examination of Quantile-Quantile (Q-Q) plots (Schielzeth et al., 2020), and statistical examination using a Shapiro-Wilk test, the following data for ball touches ( $p \le 0.005$ ) and releases ( $p \le 0.005$ ) failed to conform to a normal distribution. Technical performance data are often non-normally distributed, rendering traditional parametric statistical techniques unsuitable (Hughes & Bartlett, 2002). This contributed to the development of a dedicated protocol for establishing the agreement within such data (Cooper et al., 2007), largely based upon the non-parametric recommendations of Bland and Altman (1986; 1999), combined with the notion that 95.0% of the differences between two measures should be within an arbitrary reference value deemed to be of no practically important difference (Nevill et al., 2001). In accordance with Cooper and colleagues' (2007) recommendation for scenarios, whereby one method represents a criterion measure, a reference value of  $\pm 1$  repetition for ball touches and releases was established. The reader is referred to the original article (Cooper et al., 2007) for a detailed

explanation of the formulae used to calculate the  $P_A$  between the foot-mounted IMU and video analyses, as well as the  $P_A$  within the IMU data throughout three repeated trials of each experimental condition.

Intra-unit reliability was also quantified using the coefficient of variation (CV). For consistency and congruency, as suggested by Scott et al. (2016b), the following thresholds were used to subjectively appraise both the concurrent validity and intra-unit reliability: good (CV < 5.0%), moderate (CV = 5.0%) - 10.0%), or poor (CV > 10.0%). Expressed as a percentage, the CV was calculated as the SD of the between trial difference divided by the mean between trial difference.

# 3.3. Results

A summary of the overall concurrent validity and intra-unit reliability of the IMUs throughout all experimental conditions is presented by Table 3.3.

**Table 3.3**: A summary of the concurrent validity and intra-unit reliability of the foot-mounted IMU for quantifying ball touches and releases throughout all experimental conditions.

Variable		Concurre	ent Validi	ty		Intra-Unit Reliability						
Variable	SportsCode Mean ± SD	PlayerMaker™ Mean ± SD	P <sub>A</sub> (%)	SE (%)	PA(%) 95% CI	PlayerMaker™ Between Trial Mean ± SD Difference	P <sub>A</sub> (%)	SE (%)	P <sub>A</sub> (%) 95% CI	CV (%)		
Ball Touches (f)	$30.0\pm0.0$	$29.9\pm0.5$	95.1	0.1	95.0 - 95.3	$0.0\pm0.4$	96.9	0.0	96.8 - 96.9	1.8		
Releases (f)	$20.0\pm0.0$	$20.0\pm0.5$	97.6	0.0	97.5 - 97.7	$0.0\pm0.4$	95.9	0.2	95.5 - 96.2	2.3		

**N.B.** SD = standard deviation.  $P_A$  = proportion of agreement. SE = standard error. CI = confidence interval. CV = coefficient of variation.

#### 3.3.1. Concurrent Validity

The agreement between the foot-mounted IMUs and the observed frequency of ball touches and releases throughout each experimental condition is displayed by Table 3.4, and Table 3.5, respectively. A good  $P_A$  of 95.1% was observed between the IMUs and retrospective video analyses for the total number of ball touches performed collectively throughout all conditions. Furthermore, a good  $P_A$  of 97.6% was established between the IMUs and retrospective video analyses for the collective number of releases performed throughout all experimental conditions. These values were derived from 274 and 281 of the 288 comparative data points, for ball touches and releases respectively, being within the threshold of no practically important difference.

Variable	Condition	SportsCode Mean ± SD	PlayerMaker™ Mean ± SD	Bias	P <sub>A</sub> (%)	P <sub>A</sub> (%) 95% CI	SE (%)	P <sub>A</sub> Interpretation
Ball Touches (f)	All	$30.0\pm0.0$	$29.9\pm0.5$	-0.2	95.1	95.0 - 95.3	0.1	Good
Ball Touches (f)	DOM	$30.0\pm0.0$	$29.2\pm0.5$	-0.1	100.0	100.0 - 100.0	0.0	Good
Ball Touches (f)	NON-DOM	$30.0\pm0.0$	$29.8\pm0.6$	-0.2	95.1	94.9 - 95.4	0.2	Good
Ball Touches (f)	13.2 m	$30.0\pm0.0$	$29.9\pm0.5$	-0.1	97.2	97.0 - 97.4	0.1	Good
Ball Touches (f)	18.7 m	$30.0\pm0.0$	$29.8\pm0.5$	-0.2	95.1	94.9 - 95.4	0.2	Good

**Table 3.4:** A summary of the concurrent validity of the foot-mounted IMU for quantifying ball touches.

**N.B.** DOM = dominant foot. NON-DOM = non-dominant foot.  $P_A$  = proportion of agreement. CI = confidence interval. SE = standard error.

Variable	Condition	SportsCode Mean ± SD	PlayerMaker™ Mean ± SD	Bias	P <sub>A</sub> (%)	P <sub>A</sub> (%) 95% CI	SE (%)	P <sub>A</sub> Interpretation
Releases (f)	All	$20.0\pm0.0$	$20.0\pm0.5$	0.0	97.6	97.5 - 97.7	0.0	Good
Releases (f)	DOM	$20.0\pm0.0$	$20.0\pm0.3$	0.0	100.0	100.0 - 100.0	0.0	Good
Releases (f)	NON-DOM	$20.0\pm0.0$	$20.0\pm0.6$	0.0	95.1	94.9 - 95.4	0.2	Good
Releases (f)	13.2 m	$20.0\pm0.0$	$20.0\pm0.4$	0.0	99.3	99.2 - 99.4	0.1	Good
Releases (f)	18.7 m	$20.0\pm0.0$	$20.0\pm0.5$	0.0	96.5	96.3 - 96.8	0.11	Good

**Table 3.5:** A summary of the concurrent validity of the foot-mounted IMU for quantifying releases.

**N.B.** DOM = dominant foot. NON-DOM = non-dominant foot.  $P_A$  = proportion of agreement. CI = confidence interval. SE = standard error.

# 3.3.2. Intra-Unit Reliability

The agreement within the IMU data for ball touches and releases throughout all experimental conditions is displayed by Table 3.6, and Table 3.7, respectively. Overall  $P_A$  values of 96.9% and 95.8%, for ball touches and releases, were ascertained through the mean difference between 93 and 92 of the 96 respective data triplets being within the threshold of no practically important difference. The IMUs displayed good intra-unit reliability for monitoring ball touches and releases throughout all conditions, with respective overall CV values of 1.8% and 2.3%.

Variable	Condition	PlayerMaker™ Between Trial Mean ± SD Difference	CV (%)	P <sub>A</sub> (%)	PA (%) 95% CI	SE (%)	P <sub>A</sub> Interpretation
Ball Touches (f)	All	$0.0\pm0.4$	1.8	96.9	96.8 - 96.9	0.0	Good
Ball Touches (f)	DOM	$0.0 \pm 0.3$	1.5	100.0	100.0 - 100.0	0.0	Good
Ball Touches (f)	NON-DOM	$0.0\pm0.4$	1.8	95.9	95.0 - 96.6	0.4	Good
Ball Touches (f)	13.2 m	$0.1\pm0.4$	1.6	97.9	97.3 - 98.5	0.3	Good
Ball Touches (f)	18.7 m	$0.0 \pm 0.4$	1.8	95.8	95.0 - 96.6	0.4	Good

Table 3.6: A summary of the intra-unit reliability of the foot-mounted IMU for quantifying ball touches.

**N.B.** DOM = dominant foot. NON-DOM = non-dominant foot. CV = coefficient of variation.  $P_A$  = proportion of agreement. CI = confidence interval. SE = standard error.

Variable	Condition	PlayerMaker™ Between Trial Mean ± SD Difference	CV (%)	P <sub>A</sub> (%)	P <sub>A</sub> (%) 95% CI	SE (%)	<b>P</b> <sub>A</sub> Interpretation
Releases (f)	All	$0.0\pm0.4$	2.3	95.9	95.5 - 96.2	0.2	Good
Releases (f)	DOM	$0.0 \pm 0.2$	1.4	100.0	100.0 - 100.0	0.0	Good
Releases (f)	NON-DOM	$0.1\pm0.4$	2.9	95.9	95.0 - 96.6	0.4	Good
Releases (f)	13.2 m	$0.1\pm0.3$	1.8	95.9	95.0 - 96.6	0.4	Good
Releases (f)	18.7 m	$0.0\pm0.5$	2.7	95.9	95.0 - 96.6	0.4	Good

Table 3.7: A summary of the intra-unit reliability of the foot-mounted IMU for quantifying releases.

**N.B.** DOM = dominant foot. NON-DOM = non-dominant foot. CV = coefficient of variation.  $P_A$  = proportion of agreement. CI = confidence interval. SE = standard error.

#### 3.3.3. Comparison Between Experimental Conditions

The concurrent validity and intra-unit reliability of the foot-mounted IMUs remained within a range of 95.1% to 100.0% for ball touches and releases, indictive of consistently good agreement not only with the criterion measure, but also within the devices (Scott et al., 2016b). Trials that required the use of the dominant foot elicited 4.9% greater concurrent validity and 4.2% greater intra-unit reliability for ball touches (Figure 3.1) and releases (Figure 3.2), in comparison with trials that required the use of the non-dominant foot. Concurrent validity reduced by 2.1% and 2.8%, for ball touches and releases respectively, when the distance between players increased from 13.2 m to 18.7 m. Likewise, the intra-unit reliability for ball touches reduced by 2.1% during trials performed with 18.7 m between the players, in comparison with 13.2 m. The intra-unit reliability for releases was unaffected by the increased distance.



**Figure 3.1:** A series of modified Bland-Altman plots (Krouwer, 2008) which graphically demonstrate the concurrent validity and intra-unit reliability of the foot-mounted IMU for quantifying ball touches with the dominant (A & C) and non-dominant (B & D) foot, respectively. **N.B.** Dashed lines represent the 95.0% limits of agreement (Bland & Altman, 1986; 1999). Solid lines represent the  $\pm 1$  reference value of no practically important difference (Cooper et al., 2007).



**Figure 3.2:** A series of modified Bland-Altman plots (Krouwer, 2008) which graphically demonstrate the concurrent validity and intra-unit reliability of the foot-mounted IMU for quantifying releases with the dominant (A & C) and non-dominant (B & D) foot, respectively. **N.B.** Dashed lines represent the 95.0% limits of agreement (Bland & Altman, 1986; 1999). Solid lines represent the  $\pm 1$  reference value of no practically important difference (Cooper et al., 2007).

#### 3.4. Discussion

The utility of wearable IMUs has equipped practitioners with a wealth of objective data relating to the multifactorial determinants of soccer player performance (Cummins et al., 2013; Akenhead & Nassis, 2016). However, discerning the signal from the noise within data collected by IMUs is of critical importance to practitioners, allowing performance-related decisions to be made with an appreciation of measurement error (Malone et al., 2020).

The primary findings of this investigation are that the foot-mounted IMU displayed consistently good concurrent validity (Table 3.4 and Table 3.5), and consistently good intra-unit reliability (Table 3.6 and Table 3.7), for monitoring the 8,640 ball touches and 5,760 releases collectively performed throughout the four specified conditions within the experimental protocol (Table 3.1). Having quantified the agreement between the IMU and retrospective video analyses, overall  $P_A$  values of 95.1% and 97.6% were established for ball touches and releases respectively, representative of good concurrent validity of the IMU for quantifying both variables (Scott et al., 2016b). Furthermore, the agreement within the IMU data across three repetitions of each trial constituted  $P_A$  (CV) values of 96.9% (1.8%) and 95.8% (2.3%), for ball touches and releases respectively, indicative of good intra-unit reliability of the IMU for each metric (Scott et al., 2016b).

Technical actions performed with the players' dominant foot elicited greater concurrent validity and greater intra-unit reliability in comparison with the non-dominant foot. Although a detailed explanation is outside the scope of the current thesis, one plausible reason for this disparity may relate to the bilateral biomechanical differences that are evident during kicking (Rahnama et al., 2005). Previous research has demonstrated that kicking with the non-dominant foot results in a significantly lower ball velocity (Sinclair et al., 2014), attributed to significantly reduced knee angular velocity during extension, and subsequent reductions in foot linear velocity during ball contact (Dörge et al., 2002; Nunome et al., 2006). Furthermore, players may possess reduced neuromuscular coordination in the non-dominant limb, needed to produce the required proximal-to-distal sequencing during kicking (Kellis & Katis, 2007; Sinclair et al., 2014). These factors may reduce the magnitude of interruptions in the accelerometer and gyroscope traces, potentially contributing to abnormalities within the machine learning algorithms which automatically detect and categorise the technical actions performed (Figure 2.6) (Ofoghi et al., 2013; Halilaj et al., 2018).

The concurrent validity of the foot-mounted IMU displayed reductions of 2.1% and 2.8%, for ball touches and releases respectively, when the distance between players increased from 13.2 m to 18.7 m. However, the explanation for this may relate to methodological shortcomings within the experimental protocol, as opposed to deficiencies within the IMU. Technical actions that were performed with 18.7 m between players took place following the completion of all experimental conditions with 13.2 m between players (Table 3.1). As such, players had already performed 360 ball touches and 240 releases during the first 12 trials, prior to repeating those trials at the increased distance. Therefore, there exists the potential that neuromuscular fatigue may have impaired players' kicking mechanics during the latter trials (Kellis & Katis, 2007; Sinclair et al., 2014). Previous research has demonstrated the negative effect of neuromuscular fatigue on ball velocity during soccer kicking (Kellis et al., 2006; Russell et al., 2011; Ferraz et al., 2012) which, for reasons aforesaid, may have contributed towards irregularities within the IMU's machine learning algorithms (LeCun et al., 2015; Halilaj et al., 2018).

Despite providing an important initial understanding of the concurrent validity and intra-unit reliability of the foot-mounted IMU, the current study failed to explore the efficacy of the device during soccer tasks of higher complexity (e.g., SSG). These tasks are performed in a spatially changing environment (Singer, 2000), constituting greater perceptual-cognitive (Williams, 2000) and technical (Halouani et al., 2014) performance demands that may, in turn, alter the capabilities of the IMU. Furthermore, the protocol could be strengthened by interspersing trials with differing distances between participants (i.e., employing a cross-over design), in a similar manner to trials requiring the sole use of one foot, to alleviate the potential influence of neuromuscular fatigue upon the concurrent validity of the IMU during trials with 18.7 m between players. Lastly, the amateur players sampled during the current study may possess more pronounced bilateral biomechanical differences than their professional counterparts, which may have contributed to the reduced concurrent validity and intra-unit reliability of the IMU during trials performed with the non-dominant foot.

In considering the findings, alongside the aforementioned limitations, the current investigation has provided novel data, which indicates that the foot-mounted IMU displays promising capacity as a valid and reliable alternative method of quantifying technical actions in soccer, in the absence of semiautomatic multiple camera tracking systems or third-party data providers. Despite possessing superior validity and reliability (as discussed in Section 2.3.2.2) (Bradley et al., 2007; Liu et al., 2013), these solutions require significant financial investment, which is often unfathomable for many soccer clubs (O'Reilly et al., 2018). As such, the IMU examined during this study may represent a time-efficient and cost-effective method of measuring technical performance, with good concurrent validity and intra-unit reliability, providing data that is available immediately post-activity with a lesser financial commitment (Scott et al., 2016a; Starling & Lambert, 2018).

# 3.5. Conclusion

In conclusion, the findings of this investigation demonstrate that the examined foot-mounted IMU can be used as a tool for monitoring the frequency of ball touches and releases performed during soccer. The IMU may represent a timely addition to the athlete monitoring procedures implemented by professional soccer clubs (Weston, 2018), potentially assisting practitioners in their injury risk modification strategies (Ehrmann et al., 2016) by facilitating the construction of players' normative technical data profiles for each day within a microcycle (Akenhead & Nassis, 2016). Furthermore, the IMU may serve as a crucial time-saving mechanism, allowing practitioners to devote human resources to further their pre-match, post-match, or opposition analysis provision (Wright et al., 2013). Lastly, the IMU can assist practitioners to intervene with players who display functional performance asymmetries (Haaland & Hoff, 2003; Guilherme et al., 2015), with two-footedness being a prerequisite for successful soccer performance (Verbeek et al., 2017).

# Chapter 4:

# Quantifying Technical Actions in Professional Soccer Using Foot-Mounted Inertial Measurement Units

#### 4.1. Introduction

The multifactorial demands of professional soccer require the implementation of training programmes that combine technical, tactical, physiological, and psychological components to enhance player performance (Stølen et al., 2005). Technical (i.e., ball touches, passes, crosses, shots) and tactical components are often prioritised by coaches during in-season training (Morgans et al., 2014a), due to their association with competition success (Castellano et al., 2012; Carling, 2013). Farrow and Robertson's (2017) skill acquisition periodisation framework (discussed in detail within Section 2.4.3), has enabled practitioners to systematically adjust players' technical performance in training throughout different sports. For instance, soccer specificity may be enhanced by comparing the extent that training mimics the technical demands of competition (Pinder et al., 2011), with progression expedited by prescribing an increased frequency of technical actions (Ericsson et al., 1993). However, technical actions are consistently neglected by practitioners during player monitoring processes (Akenhead & Nassis, 2016; Malone et al., 2020), despite contributing to players' overall external training load (Bradley & Ade, 2018).

The monitoring of technical actions is pertinent because the frequency of these actions executed by professional players during match-play has risen over time (see Section 2.2). Barnes et al. (2014), reported that the frequency of ball touches and passes executed by EPL players increased, by 10.5% and 39.9% respectively, over seven consecutive seasons. In the 2019/2020 season, UEFA Champions League players typically performed  $60.2 \pm 20.7$  ball touches and  $50.1 \pm 25.7$  releases (i.e., passes, crosses, shots, clearances) per match (Table 2.4) (Yi et al., 2020). Despite such insights into matchplay, examinations of technical actions during training scarcely appear within the literature (Liu et al., 2016; Bradley & Ade, 2018). Quantifying technical actions often requires complex and expensive infrastructure, such as semi-automatic multiple camera tracking systems (e.g., ProZone<sup>®</sup>, Castellano et al., 2014) or local positioning systems (e.g., Inmotio, Frencken et al., 2010; Kinexon, Hoppe et al., 2018). Although these systems provide data that contextualises the various determinants of player performance (Bradley & Ade, 2018), the significant financial investment required hinders the transferability of such methods to the training environment (Akenhead & Nassis, 2016; Cardinale & Varley, 2017). In this setting, manual coding has been the prominent approach to assessing players' technical performance (Wright et al., 2013), which not only quantifies the specific technical actions performed (Wright et al., 2016), but also provides an understanding of players' pitch location (Taylor et al., 2010) and associated action success (Bateman & Jones, 2019). Yet, this process needs highly trained operators to limit measurement error (O'Donoghue, 2007) and to achieve sufficient validity and reliability (Francis et al., 2019; Gong et al., 2019). Moreover, the substantial human resources required has compelled practitioners to explore alternative approaches for quantifying technical actions during training (Carling et al., 2014; Robertson, 2020). As a solution to these problems, the implementation of wearable microtechnology, attached to players' boots (Edwards et al., 2019), may represent a time-efficient and cost-effective option for monitoring technical actions during weekly training microcycles (Chambers et al., 2015; Nedergaard et al., 2017).

Quantifying technical actions during training would provide a broader understanding of the periodisation strategies used to prepare professional players for competition. Throughout a typical microcycle, external training load markers (e.g., total distance, mean speed) are consistently at their lowest on the day immediately before competition (Anderson et al., 2015; Malone et al., 2015; Stevens et al., 2017; Martín-García et al., 2018), with practitioners adopting this tapering approach to physically unload players and increase readiness for competition (Malone et al., 2015; Owen et al., 2017). Anecdotally, this unloading coincides with training becoming more technically and tactically oriented (Martín-García et al., 2018; Walker & Hawkins, 2018). However, empirical evidence to support this is lacking, necessitating an examination of the technical actions performed throughout professional soccer training microcycles.

The periodisation of technical actions provides a macro view of training. However, the withinsession distribution of technical actions also warrants attention. Despite numerous studies examining technical actions during specific training drills (e.g., SSG) in isolation (Fradua et al., 2013; Aguiar et al., 2015), little consideration has been given to the effect of drill category on the technical actions executed by professional players (Barrett et al., 2020). Understanding these effects would allow practitioners to manipulate players' technical actions to satisfy the aforementioned principles of skill acquisition periodisation (Farrow & Robertson, 2017). Furthermore, to facilitate evidence-based decisions regarding the inclusion of drills to achieve training objectives (Jaspers et al., 2017), and to supplement coaches' feedback by providing objective insights into players' technical actions (Stodter & Cushion; 2019; Nosek et al., 2021), the aim of the current study was to quantify the withinmicrocycle, inter-positional, and between-drill differences in the frequency of technical actions performed during professional soccer training using foot-mounted IMUs.

# 4.2. Methods

## 4.2.1. Experimental Design

Technical actions were quantified during training sessions throughout a 24-week mid-season (September to February) period of the 2019/2020 EFL Championship season (Figure 4.1), prior to competition disruption (FA, 2020a). This phase ensured minimal changes to players' physiological fitness, such as those that typically occur during the transition from pre-season to in-season, where head coaches emphasise the continuation of physical conditioning (Malone et al., 2015). Two microcycles were excluded as they fell within the FIFA International Match Calendar (Malone et al., 2015; Stevens et al., 2017). Training sessions within one microcycle were categorised in relation to the number of days prior to a competitive fixture (i.e., MD minus day number [MD - n]) (Malone et al., 2015). Microcycles encompassing one fixture (n = 13, 54.2%) typically contained four training sessions, with MD - 3 being a recovery day for all players. Fixtures were followed by a recovery day for all players. According to their primary objective, training drills were assigned one of the following categories: position specific; possession; SSG; tactical; technical; or warm-up (Table 4.1).

Preparation phase	-	Competition phase													
1	2	3	4	5	6	1 1 7									
						DNC									

**Figure 4.1:** A schematic of the block periodised preparation system employed by the soccer club (Issurin, 2016). **N.B.** Numbered blocks represent each mesocycle, encompassing six smaller blocks representative of weekly microcycles. The second and seventh mesocycles, at the beginning and end of the competition phase, were removed. The 24 microcycles that were selected for analysis are depicted within the dashed box. The club did not complete (DNC) the final four microcycles.

**Table 4.1:** The operational definitions of six categories of training drill that were prescribed throughout

 the training programme (Barrett et al., 2020).

Drill Category	<b>Operational Definition</b>
Position Specific	Drills aimed at specific units of the team (i.e., defenders, midfielders, and strikers), with players separated according to their position and coached as a unit or an individual.
Possession	Drills designed to mimic similar demands of match-play, with the aim being to keep the ball away from the opposing team, with no goals to score in.
SSG	Drills expected to replicate the demands of match-play, with a reduced number of players, reduced pitch size, and specific rules to elicit the required intensity, with goals to score in.
Tactical	Drills intended to educate players as to the tactical roles they occupy within the team shape, inclusive of open play and set-piece exercises.
Technical	Drills designed to work on a soccer-specific skill (e.g., dribbling, passing, crossing, shooting), working as an entire group.
Warm-Up	Drills intended to prepare the players, both physically and technically, for the forthcoming training session.

#### 4.2.2. Exclusion Criteria

Players were required to have completed three full pitch-based sessions on each training day, and three repetitions of each drill, to facilitate comparative analyses. This resulted in 27 players (e.g., academy scholars, trialists, players transferred in/out) being removed from the dataset through their intermittent involvement during the training programme. For eligible players, the 24-week data collection period yielded 8,535 drill observations. 9.3% (n = 796) of these were removed having imposed various exclusion criteria (Figure 4.2) derived from comparable longitudinal monitoring studies (Malone et al., 2015; Stevens et al., 2017).



**Figure 4.2:** A flow chart of the data exclusion process derived from comparable longitudinal player monitoring studies (Malone et al., 2015; Stevens et al., 2017).

A total of 66 training sessions, comprising 7,739 individual player observations, were included for analysis. Players completed a mean of  $47.7 \pm 13.2$  training sessions, with  $7.4 \pm 2.1$  drill observations per session. Sessions had a ball-in-play time of  $61.8 \pm 5.5$  minutes, with recovery periods removed to provide an accurate representation of training intensity (Wass et al., 2020). Each player completed 351.8  $\pm$  98.1 drills during the study, which did not influence the training content delivered.

## 4.2.3. Participants

Twenty-one professional soccer players (mean  $\pm$  SD age: 24.4  $\pm$  3.1 years; stature: 183.0  $\pm$  8.1 cm; mass: 80.6  $\pm$  9.6 kg), from one EFL Championship club, participated in this study. The sample size was constrained by the finite number of players with professional contracts, who were available to participate in training, that satisfied the aforementioned exclusion criteria. As categorised by the head coach, who typically employed a 4-2-3-1 formation, the sample of players comprised five CD, five WD, six CM, three WM, and two ST. The head coach and coaching staff remained consistent throughout, alleviating the potential influence of a change in head coach on the technical requirements of the training programme (Whitehead et al., 2018). This study obtained institutional ethical approval (FHS200), with data collected as part of daily player monitoring procedures.

#### 4.2.4. Inertial Measurement Units

Technical actions were quantified using commercially available foot-mounted IMUs (PlayerMaker<sup>TM</sup>, Tel Aviv, Israel). Each IMU incorporated two components from the MPU-9150 multi-chip motion tracking module (InvenSense, California, USA), being a 16 g triaxial piezoelectric accelerometer and a  $2000^{\circ} \cdot \text{s}^{-1}$  triaxial piezoelectric gyroscope. The IMU sampled at a rate of 1000 Hz, with data filtered using machine learning algorithms at 250 Hz (Figure 2.6). Housed in manufacturer-supplied tightly-fitting silicone straps, each player was equipped with two IMUs (one for each foot), which were located at the lateral malleoli over the player's boots (Figure 2.7). To diminish issues related to inter-unit reliability, players used the same IMUs throughout the data collection period (Buchheit et al., 2014a; Malone et al., 2020).

#### 4.2.5. Statistical Analysis

Having verified the assumption of normality using a Q-Q plot (Schielzeth et al., 2020), general linear modelling was conducted within Statistical Package for the Social Sciences (SPSS) (v. 26; IBM, Chicago, USA) to establish estimated marginal mean, standard error (SE), and CI values for the four fixed variables of interest: ball touches, releases, ball touches per minute, releases per minute. Random variables (e.g., player age, calendar month) were screened for covariance (Hopkins & Wolfinger, 1998), with Wald Z statistics ( $p \ge 0.005$ ) indicating that no random intercept was required. In the event of a statistically significant *F* ratio, Sidak adjusted post-hoc pairwise comparisons between the estimated marginal means were analysed. Cohen's d ES statistics, using the pooled SD as the denominator, were computed to ascertain the magnitude of the within-microcycle, inter-positional, and between-drill differences, with the following descriptors attached: trivial ( $\le 0.20$ ); small ( $\ge 0.21 - 0.60$ ); moderate ( $\ge 0.61 - 1.20$ ); large ( $\ge 1.21 - 2.00$ ); very large ( $\ge 2.01$ ) (Hopkins et al., 2009). Two-tailed statistical significance was established as  $p \le 0.005$ .

# 4.3. Results

#### 4.3.1. Fixture Proximity

There were main effects of fixture proximity on the frequency of technical actions ( $F_{(4, 1019)} = 1,705.05$  - 2,026.17,  $p \le 0.001$ ; ES = 0.01 - 0.89) (Table 4.2), inter-positional differences in the absolute frequency of ball touches and releases ( $F_{(20, 1003)} = 347.19 - 416.34, p \le 0.001$ ; ES = 0.00 - 0.83) (Figure 4.3) and the relative frequency of ball touches per minute and releases per minute ( $F_{(20, 1003)} = 361.10 - 446.99, p \le 0.001$ ; ES = 0.01 - 0.73) (Figure 4.4).

#### 4.3.2. Playing Position

There were main effects of playing position ( $F_{(5, 1018)} = 1,301.82 - 1,697.79, p \le 0.001$ ; ES = 0.01 - 0.64) on the frequency of ball touches, releases, ball touches per minute, and releases per minute performed during a typical training session (Table 4.3).

# 4.3.3. Drill Category

There were main effects of drill category (F [6, 7728] = 3,801.45 - 4,314.05, p  $\le$  0.001; ES = 0.21 - 4.35) on the frequency of ball touches and releases (Table 4.4), on the relative frequency of ball touches per minute and releases per minute (F [6, 7728] = 3,709.50 - 4,929.72, p  $\le$  0.001, ES = 0.04 - 3.04) (Figure 4.5), and on the inter-positional differences in the relative frequency of ball touches per minute and releases per minute (F [20, 1003] = 361.10 - 446.99, p  $\le$  0.001; ES = 0.00 - 0.43) (Figure 4.6). The within-microcycle prevalence of each category of training drill is depicted by Table 4.5.

		Overall		]	MD - 5			MD - 4		]	MD - 2		]	MD - 1	
Variable	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI
Duration (min)	62.5	0.8	61.0 - 64.1	41.5 4 <sup>L</sup> 2 <sup>L</sup> 1 <sup>M</sup>	2.1	37.3 - 45.7	76.6 5 <sup>L</sup> 1 <sup>M</sup>	1.8	73.1 - 80.1	70.8 5 <sup>L</sup> 1 <sup>S</sup>	1.4	68.1 - 73.5	57.8 5 <sup>M</sup> 4 <sup>M</sup> 2 <sup>S</sup>	1.1	55.7 - 59.9
Ball Touches (f)	209.9	2.4	205.3 - 214.6	181.9 4 <sup>8</sup> 2 <sup>8</sup> 1 <sup>8</sup>	7.0	168.2 - 195.7	209.0 5 <sup>8</sup>	5.9	197.4 - 220.5	208.4 5 <sup>8</sup>	4.4	199.7 - 217.1	218.0 5 <sup>8</sup>	3.5	211.2 - 224.8
Releases (f)	103.0	1.3	100.4 - 105.5	80.9 4 <sup>8</sup> 2 <sup>8</sup> 1 <sup>M</sup>	3.8	73.6 - 88.3	99.7 5 <sup>8</sup> 1 <sup>8</sup>	3.2	93.5 - 105.9	100.6 5 <sup>8</sup> 1 <sup>8</sup>	2.4	95.9 - 105.2	110.8 5 <sup>M</sup> 4 <sup>S</sup> 2 <sup>S</sup>	1.9	107.2 - 114.5
Ball Touches (f·min⁻¹)	3.1	0.0	3.1 - 3.2	3.8 4 <sup>M</sup> 2 <sup>M</sup> 1 <sup>M</sup>	0.1	3.6 - 4.0	2.8 5 <sup>M</sup> 2 <sup>S</sup> 1 <sup>S</sup>	0.1	2.6 - 2.9	3.1 5 <sup>M</sup> 4 <sup>S</sup>	0.1	3.0 - 3.2	3.1 5 <sup>M</sup> 4 <sup>S</sup>	0.1	3.0 - 3.2
Releases (f·min <sup>-1</sup> )	1.5	0.0	1.4 - 1.5	1.7 4 <sup>M</sup> 1 <sup>S</sup>	0.1	1.5 - 1.8	1.3 5 <sup>M</sup> 2 <sup>S</sup> 1 <sup>S</sup>	0.0	1.2 - 1.4	1.5 4 <sup>8</sup>	0.0	1.4 - 1.6	1.5 5 <sup>8</sup> 4 <sup>8</sup>	0.0	1.4 - 1.5

**Table 4.2:** Estimated marginal mean values representative of the absolute frequency of ball touches and releases, and the relative frequency of ball touches and releases per minute of ball-in-play time, performed by professional soccer players on each training day within a typical weekly microcycle.

**N.B.** EM = estimated marginal. SE = standard error. CI = confidence intervals. MD = match day. Statistically significant differences ( $p \le 0.005$ ) are depicted in bold: **5** = MD - 5; **4** = MD - 4; **2** = MD - 2; and **1** = MD - 1. Observed magnitude of effects are denoted as:  $[^{T}]$  = trivial;  $[^{S}]$  = small;  $[^{M}]$  = moderate;  $[^{L}]$  = large; and  $[^{V}]$  = very large.



Figure 4.3: Estimated marginal mean ( $\pm$  SE) inter-positional differences in the absolute frequency of ball touches and releases performed by professional soccer players on each training day within a typical weekly microcycle. N.B. Each bar represents one playing position. Lighter shaded areas represent ball touches. Darker shaded areas represent releases. MD = match day. Statistically significant differences ( $p \le 0.005$ ) are displayed above SE bars. \* = statistically significant difference to all other playing positions. \*<sup>CD</sup> = statistically significant difference to central defenders. \*<sup>WD</sup> = statistically significant difference to wide defenders. \*<sup>CM</sup> = statistically significant difference to wide midfielders. \*<sup>ST</sup> = statistically significant difference to strikers.



Figure 4.4: Estimated marginal mean ( $\pm$  SE) inter-positional differences in the relative frequency of ball touches and releases, per minute of ball-in-play time, performed by professional soccer players on each training day within a typical weekly microcycle. N.B. Each bar represents one playing position. Lighter shaded areas represent ball touches per minute. Darker shaded areas represent releases per minute. Statistically significant differences ( $p \le 0.005$ ) are displayed above SE bars. MD = match day. \* = statistically significant difference to all other playing positions. \*<sup>CD</sup> = statistically significant difference to central defenders. \*<sup>WD</sup> = statistically significant difference to wide midfielders. \*<sup>ST</sup> = statistically significant difference to strikers.

**Table 4.3:** Estimated marginal mean values representative of the inter-positional differences in the absolute frequency of ball touches and releases, and the relative frequency of ball touches and releases per minute of ball-in-play time, performed by professional soccer players during a typical training session.

		CD			WD			СМ			WM			ST	
Variable	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI
Ball Touches (f)	206.1	4.8	196.7 - 215.4	200.9 см <sup>s</sup>	4.8	191.5 - 210.2	221.9 wd <sup>s</sup> st <sup>s</sup>	4.4	213.3 - 230.4	218.3	6.4	205.6 - 230.9	195.4 см <sup>s</sup>	7.5	180.7 - 210.2
Releases (f)	102.2	2.6	97.1 - 107.3	97.5 см <sup>s</sup>	2.6	92.4 - 102.6	108.3 wd <sup>s</sup>	2.4	103.6 - 112.9	106.9	3.5	100.0 - 113.8	97.2	4.1	89.2 - 105.3
Ball Touches ( <i>f</i> ∙min <sup>-1</sup> )	2.9 wd <sup>s</sup> см <sup>s</sup>	0.1	2.7 - 3.0	3.2 Cd <sup>s</sup> st <sup>s</sup>	0.1	3.0 - 3.3	3.4 cd <sup>s</sup> st <sup>m</sup>	0.1	3.3 - 3.5	3.2 st <sup>s</sup>	0.1	3.0 - 3.4	2.7 wd <sup>s</sup> см <sup>m</sup> wm <sup>s</sup>	0.1	2.5 - 2.9
Releases (f·min <sup>-1</sup> )	1.4 см <sup>s</sup>	0.0	1.3 - 1.5	1.5 st <sup>s</sup>	0.0	1.4 - 1.6	1.6 ср <sup>8</sup> st <sup>8</sup>	0.0	1.5 - 1.7	1.4	0.0	1.3 - 1.5	1.3 wd <sup>s</sup> см <sup>s</sup>	0.1	1.2 - 1.4

**N.B.** EM = estimated marginal. SE = standard error. CI = confidence intervals. Statistically significant differences ( $p \le 0.005$ ) are depicted in bold: **CD** = central defenders;

WD = wide defenders; CM = central midfielders; WM = wide midfielders; and ST = strikers. Observed magnitude of effects are denoted as:  $[^{T}]$  = trivial;  $[^{S}]$  = small;  $[^{M}]$  =

moderate;  $[^{L}] =$ large; and  $[^{V}] =$ very large.

**Table 4.4:** Estimated marginal mean values representative of the differences in the absolute frequency of ball touches and releases, and the relative frequency of ball touches and releases per minute of ball-in-play time, performed by professional soccer players throughout each category of training drill.

	Position S	Specific		Poss	ession		880	G		Tac	ctical		Tech	nical		Wa	rm-Up	
v ariable	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI	EM Mean	SE	95% CI
Duration (min)	27.0 pos <sup>v</sup> ssg <sup>v</sup> tac <sup>v</sup> tec <sup>v</sup> wu <sup>v</sup>	0.2	26.6 - 27.5	12.7 ps <sup>v</sup> ssg <sup>l</sup> tac <sup>s</sup> tec <sup>m</sup> wu <sup>s</sup>	0.2	12.3 - 13.2	2.7 ps <sup>v</sup> pos <sup>l</sup> tac <sup>l</sup> tec <sup>l</sup> wu <sup>v</sup>	0.1	2.5 - 2.8	10.3 ps <sup>v</sup> pos <sup>s</sup> ssg <sup>l</sup> tec <sup>T</sup> wu <sup>M</sup>	0.2	10.0 - 10.6	9.4 ps <sup>v</sup> pos <sup>s</sup> ssg <sup>l</sup> tac <sup>t</sup> wu <sup>m</sup>	0.2	9.1 - 9.7	15.2 ps <sup>v</sup> pos <sup>s</sup> ssg <sup>v</sup> tac <sup>m</sup> tec <sup>m</sup>	0.2	14.7 - 15.6
Ball Touches ( <i>f</i> )	56.4 pos <sup>m</sup> ssg <sup>v</sup> tac <sup>l</sup> tec <sup>s</sup> wu <sup>v</sup>	0.9	54.6 - 58.2	30.9 ps <sup>m</sup> ssg <sup>m</sup> tac <sup>m</sup> tec <sup>l</sup> wu <sup>v</sup>	1.0	28.9 - 32.8	6.9 ps <sup>v</sup> pos <sup>m</sup> tac <sup>s</sup> tec <sup>v</sup> wu <sup>v</sup>	0.4	6.2 - 7.6	12.4 ps <sup>l</sup> pos <sup>m</sup> ssg <sup>s</sup> tec <sup>v</sup> wu <sup>v</sup>	0.7	11.1 - 13.6	61.2 ps <sup>\$</sup> pos <sup>L</sup> ssg <sup>V</sup> tac <sup>V</sup> wu <sup>L</sup>	0.7	59.7 - 62.6	104.2 ps <sup>v</sup> pos <sup>v</sup> ssg <sup>v</sup> tac <sup>v</sup> tec <sup>l</sup>	0.9	102.4 - 106.0
Releases (f)	28.3 pos <sup>l</sup> ssg <sup>v</sup> tac <sup>l</sup> tec <sup>s</sup> wu <sup>v</sup>	0.5	27.3 - 29.3	13.3 ps <sup>l</sup> ssg <sup>m</sup> tac <sup>m</sup> tec <sup>l</sup> wu <sup>v</sup>	0.5	12.3 - 14.4	2.8 ps <sup>v</sup> pos <sup>m</sup> tac <sup>s</sup> tec <sup>v</sup> wu <sup>v</sup>	0.2	2.4 - 3.2	5.4 ps <sup>l</sup> pos <sup>m</sup> ssg <sup>s</sup> tec <sup>v</sup> wu <sup>v</sup>	0.4	4.7 - 6.1	31.0 ps <sup>8</sup> pos <sup>l</sup> ssg <sup>v</sup> tac <sup>v</sup> wu <sup>l</sup>	0.4	30.2 - 31.8	55.2 ps <sup>v</sup> pos <sup>v</sup> ssg <sup>v</sup> tac <sup>v</sup> tec <sup>L</sup>	0.5	54.2 - 56.1
Ball Touches (f min <sup>-1</sup> )	2.4 tac <sup>s</sup> tec <sup>l</sup> wu <sup>v</sup>	0.1	2.2 - 2.5	2.5 ssg <sup>t</sup> tac <sup>m</sup> tec <sup>v</sup> wu <sup>v</sup>	0.1	2.3 - 2.6	2.2 pos <sup>t</sup> tac <sup>s</sup> tec <sup>v</sup> wu <sup>v</sup>	0.0	2.1 - 2.2	1.2 PS <sup>M</sup> POS <sup>M</sup> SSG <sup>S</sup> TEC <sup>V</sup> WU <sup>V</sup>	0.1	1.1 - 1.3	6.2 ps <sup>v</sup> pos <sup>v</sup> ssg <sup>v</sup> tac <sup>v</sup> wu <sup>s</sup>	0.1	6.1 - 6.3	6.8 ps <sup>v</sup> pos <sup>v</sup> ssg <sup>v</sup> tac <sup>v</sup> tec <sup>s</sup>	0.1	6.6 - 6.9
Releases (f∙min <sup>-1</sup> )	$\frac{1.2}{\text{ssg}^{S}\text{tac}^{M}\text{tec}^{L}\text{wu}^{V}}$	0.0	1.2 - 1.3	$\frac{1.1}{\text{ssg}^{T} \text{tac}^{S} \text{tec}^{V} \text{wu}^{V}}$	0.0	1.0 - 1.2	0.9 ps <sup>s</sup> pos <sup>s</sup> tac <sup>s</sup> tec <sup>v</sup> wu <sup>v</sup>	0.0	0.9 - 0.9	0.5 ps <sup>m</sup> pos <sup>s</sup> ssg <sup>s</sup> tec <sup>v</sup> wu <sup>v</sup>	0.0	0.5 - 0.6	3.1 ps <sup>v</sup> pos <sup>l</sup> ssg <sup>v</sup> tac <sup>v</sup> wu <sup>s</sup>	0.0	3.1 - 3.2	3.6 ps <sup>v</sup> pos <sup>v</sup> ssg <sup>v</sup> tac <sup>v</sup> tec <sup>s</sup>	0.0	3.6 - 3.7

**N.B.** EM = estimated marginal. SE = standard error. CI = confidence intervals. Statistically significant differences ( $p \le 0.005$ ) are depicted in bold: **PS** = position specific;

**POS** = possession; **SSG** = small-sided games; **TAC** = tactical; **TEC** = technical; and **WU** = warm-up. Observed magnitude of effects are denoted as:  $[^{T}]$  = trivial;  $[^{S}]$  = small;

 $[^{M}]$  = moderate;  $[^{L}]$  = large; and  $[^{V}]$  = very large.


Figure 4.5: Estimated marginal mean ( $\pm$  SE) differences in the relative frequency of ball touches and releases, per minute of ball-in-play time, performed by professional soccer players during each category of training drill. N.B. Lighter shaded areas represent ball touches per minute. Darker shaded areas represent releases per minute. Statistically significant differences ( $p \le 0.005$ ) are displayed above SE bars. \* = statistically significant difference to all other drill categories. \*<sup>PS</sup> = statistically significant difference to possession. \*<sup>SSG</sup> = statistically significant difference to actical. \*<sup>TEC</sup> = statistically significant difference to technical. \*<sup>WU</sup> = statistically significant difference to warm-up.



8.0

**Drill Category** 

Figure 4.6: Estimated marginal mean ( $\pm$  SE) inter-positional differences in the relative frequency of ball touches and releases, per minute of ball-in-play time, performed by professional soccer players during each category of training drill. N.B. Each bar represents one playing position. Lighter shaded areas represent ball touches per minute. Darker shaded areas represent releases per minute. Statistically significant differences ( $p \le 0.005$ ) are displayed above SE bars. \* = statistically significant difference to all other drill categories. \*<sup>PS</sup> = statistically significant difference to possible significant difference to SSG. \*<sup>TAC</sup> = statistically significant difference to tactical. \*<sup>TEC</sup> = statistically significant difference to technical. \*<sup>WU</sup> = statistically significant difference to warm-up.

Drill Category –	Fixture Proximity			
	MD - 5	MD - 4	MD - 2	MD - 1
Position Specific	14.0	21.1	38.8	26.0
Possession	33.4	37.8	22.6	6.2
SSG	32.9	18.7	11.6	36.8
Tactical	9.5	32.5	32.3	25.7
Technical	27.4	22.3	25.4	24.8
Warm-Up	10.6	28.3	19.1	42.0

**Table 4.5:** The weighted percentage distribution of each category of training drill prescribed during a typical weekly microcycle.

**N.B.** MD = match day. SSG = small-sided games.

## 4.4. Discussion

The primary findings of this study were: (i) players typically performed the most ball touches and releases on MD - 1, (ii) training sessions on MD - 5 elicited the most ball touches per minute and releases per minute, (iii) CM generally performed the highest frequency of ball touches, releases, ball touches per minute and releases per minute, (iv) the specificity of SSG for replicating the positional technical demands of match-play may be limited, and (v) regardless of playing position, the fewest ball touches per minute and releases per minute were observed during tactical drills.

Previous research has demonstrated that players exhibit the lowest external training load on the day immediately preceding competition (Anderson et al., 2015; Malone et al., 2015; Stevens et al., 2017; Martín-García et al., 2018). Conversely, the current study noted that the frequency of technical actions performed during a typical microcycle peaked on MD - 1 (Table 4.2), which supports the notion that, to physically unload players as competition approaches (Malone et al., 2015; Owen et al., 2017),

training objectives become more technical and tactical in nature (Martín-García et al., 2018; Walker & Hawkins, 2018). It would appear that the coaches sought to facilitate this pre-competition physical unloading by prescribing a greater proportion of position specific, tactical, and warm-up drills on this day (Table 4.5), with such drills demonstrating significantly lower external training load markers (e.g., total distance per minute, high-speed running distance per minute) than SSG (Barrett et al., 2020). However, training sessions on MD - 1 resulted in the average player performing almost 4 times the frequency of ball touches, and more than double the frequency of releases, compared to previously reported match-play data from semi-automatic multiple camera tracking systems (Yi et al., 2020). Although previous research has emphasised caution when comparing data from different monitoring systems (Buchheit et al., 2014b; Taberner et al., 2020), the foot-mounted IMU is not currently permitted during match-play under the Laws of the Game (Law 4.4; IFAB, 2020). Therefore, albeit tentatively, the current study begins to question whether players' readiness for the impending fixture may have been inadvertently compromised (Anderson et al., 2016; Kelly et al., 2020), given the potential for neuromuscular fatigue attributed to the heightened frequency of technical actions performed (Guex & Millet, 2013, Silva et al., 2018). Nevertheless, the IMU could not differentiate between the types of release performed, nor did the current study examine players' shank angular velocity during kicking (Lees et al., 2010), which has demonstrated fatigue-related decrements (Ferraz et al., 2012; 2019). Future research considering the magnitude of players' releases may, therefore, provide an insight into the metabolic cost implications of performing specific technical actions (Osgnach et al., 2010; Russell et al., 2011; Walker et al., 2016). By understanding the resulting biomechanical load imposed on the musculoskeletal system pre-competition (Vanrenterghem et al., 2017), and associated mechanobiological response (Wisdom et al., 2015), practitioners would be better placed to gauge players' holistic readiness to perform in conjunction with current monitoring systems (Bradley & Ade, 2018; Verheul et al., 2020).

Relative to ball-in-play time, training sessions on MD - 5 elicited the most ball touches per minute and releases per minute (Figure 4.4). The greatest proportion of technical drills was also observed on MD - 5 (Table 4.5), perhaps delivered in an attempt to compensate players for the lack of technical stimuli through not participating in competition (Morgans et al., 2018). Although this study

did not account for levels of match participation, which has demonstrated large (ES = 2.00 - 2.50) effects on external training load markers (Anderson et al., 2015), the training group on MD - 5 often comprised non-starting (i.e., those who started less than 30.0% of matches) and fringe players (i.e., those who started between than 30.0% and 60.0% of matches), with those who started the previous fixture performing recovery activities (Morgans et al., 2014a; Anderson et al., 2016). Practitioners frequently prescribe 'top-up' training immediately after a fixture to atone for the insufficient external training load encountered by partial-match and unused substitute players (Hills et al., 2018; Buchheit, 2019; Buckthorpe et al., 2019). However, such training is solely physical in nature, with players rarely exposed to supplementary technical activities (Hills et al., 2020a). This may be due to governing body pitch-usage restrictions permitting only 15 minutes of post-match activity (Rule 23.11i, FA, 2020b), team travel requirements (Hills et al., 2020a) or a lack of available coaching staff (Hills et al., 2020b). As such, it would appear that practitioners attempt to limit the consequences of reversibility (Farrow & Robertson, 2017), by utilising technical drills on MD - 5 to provide non-starting and fringe players with sufficient perceptual-cognitive stimuli that is crucial for technical performance (Reilly et al., 2000; Williams & Hodges, 2005). Nonetheless, the alternative tactical systems (Whitehead et al., 2018) and within-microcycle schedules (Malone et al., 2015), employed by head coaches may influence technical performance during specific training programmes, limiting the generalisability of these results (Dalton-Barron et al., 2020).

Inter-positional differences in the technical actions of match-play are well documented within the literature (Ade et al., 2016; Baptista et al., 2018). However, prior to the current investigation, research examining these differences in the training environment was scarce. This study reported trivialto-moderate (ES = 0.01 - 0.64) inter-positional differences in the technical actions of professional soccer training, with CM performing the most absolute and relative ball touches and releases during a typical training session (Table 4.3). This suggests that the technical actions performed by CM during training are somewhat specific to those experienced during competition (Farrow & Robertson, 2017), with this position typically performing the most ball touches and releases per match (Table 2.4) (Yi et al., 2020). This is likely related to the tactical responsibilities of CM (Dellal et al., 2011a), which primarily involves coordinating attacking play and creating goal scoring opportunities (Gonçalves et al., 2014; Bush et al., 2015). For instance, regardless of match status, 61.0% of passes originate from the midfield third of the pitch (Taylor et al., 2010), likely contributing to CM demonstrating trivial differences in frequency of technical actions between playing at home versus playing away, and trivial differences when playing against a higher quality of opposition (Yi et al., 2020). This highlights the importance of training specificity for CM (Farrow & Robertson, 2017), given the apparent stability of the technical actions performed by this position during match-play.

To simultaneously provide players with technical, tactical, physiological, and psychological stimuli similar to that encountered during competition, SSG are routinely employed in professional soccer training (Hill-Hass et al., 2011; Halouani et al., 2014; Bujalance-Moreno et al., 2019). Indeed, SSG accounted for 49.5% of individual drill observations during the current investigation, with the highest proportion being observed on MD - 1 (Table 4.5). The trivial-to-small (ES = 0.00 - 0.35) interpositional differences in the frequency of ball touches per minute and releases per minute observed during SSG would imply that the specificity of these drills for replicating the inter-positional technical actions of match-play may be limited (Farrow & Robertson, 2017). For example, the only small differences during SSG were observed within CM, who performed more ball touches than CD and ST (Figure 4.6). For all playing positions, SSG during training evoked more ball touches per minute and releases per minute than match-play (Yi et al., 2020), suggesting that SSG may facilitate progression through the elevated frequency of technical actions performed (Farrow & Robertson, 2017), alongside the concurrent decision-making and perceptual demands of these drills (Sampaio & Maçãs, 2012; Aguiar et al., 2015). However, comparisons between training and match-play should be interpreted with caution, given the problematic nature of quantifying performance with different systems in different environments (Buchheit et al., 2014b). Future research should explore the agreement between the footmounted IMUs and semi-automatic multiple camera tracking systems, to determine whether these approaches can be used interchangeably throughout training and match-play (Taberner et al., 2020).

Drill category displayed trivial-to-very large (ES = 0.04 - 3.04) effects on the relative frequency of technical actions performed during training (Figure 4.5; Table 4.4). Tactical drills (e.g., team shape, set pieces) are arguably the most important training modality in professional soccer, with players' tactical roles being a powerful determinant of match performance (Bradley & Ade, 2018). This study observed that, for all positions, the fewest ball touches per minute and releases per minute were observed during tactical drills. These drills are intermittent in nature (Siegle & Lames, 2012), with coaches frequently interrupting to provide instruction and management-related information (Ford et al., 2010). Although instruction and management are crucial for delivering tactical messages (Cushion & Jones, 2001), previous research has demonstrated the potential issues related to interrupting practice too frequently (Williams & Hodges, 2005), which perhaps contributed to the lowest relative technical stimuli being provided by tactical drills. Therefore, practitioners should seek alternative exercise modalities, such as incorporating technical actions within warm-up drills, should a high technical output be required from a particular session.

## 4.5. Conclusion

In conclusion, this investigation has provided a novel understanding of within-microcycle, interpositional, and between-drill differences in the technical actions of professional soccer training, which may be especially relevant to researchers and practitioners alike. Although the magnitude of players' releases was not quantified, which may yield a broader understanding of the metabolic and mechanobiological implications of performing technical actions (Walker et al., 2016; Vanrenterghem et al., 2017), the insights provided by this investigation have the potential to inform pre-competition recovery strategies to negate the neuromuscular fatigue possibly induced through increased technical activity on MD - 1 (Rey et al., 2012a; 2012b; Nédélec et al., 2015a). Lastly, coaches could manipulate the frequency (e.g., CM performing additional releases during possession drills), and complexity (ST required to hit certain zones during position specific drills), of technical actions during training to provide an optimal challenge point that enhances the positional specificity, and promotes progression, according to the principles of skill acquisition periodisation (Section 2.4.3) (Guadagnoli & Lee, 2004; Farrow & Robertson, 2017; Mujika et al., 2018).

# **Chapter 5: General Discussion**

#### 5.1. Synthesis of Findings

The following chapter intends to provide an overview of the conceptual and theoretical interpretations of the data originating from this thesis, in relation to the specific aims and objectives outlined at the conclusion of Chapter 1. The aforesaid purpose of this research project was to examine the efficacy and utility of a foot-mounted IMU for measuring the frequency of technical actions performed during professional soccer training. An appraisal of the aims and objectives of this project is featured below (Section 5.1.1), which precedes a general discussion of the findings of each experimental study (Section 5.2), the limitations encountered during this thesis (Section 5.3), and directions for future research (Section 5.4).

#### 5.1.1. Evaluation of Aims and Objectives

The aim of the first experimental study conducted within this thesis (Chapter 3), was to establish the concurrent validity and intra-unit reliability of a foot-mounted IMU for measuring the frequency of technical actions performed during soccer training activities. The previous 20 years has seen a substantial increase in the use of wearable microtechnology for monitoring professional soccer player performance during training and match-play. However, an examination of the validity and reliability of wearable MEMS is crucial to the interpretation of the data collected by such devices, enabling practitioners to recognise the signal from the noise and avoid making evidence-based decisions based upon potentially erroneous data. As specified in Section 5.2.1, the data presented in Chapter 3 demonstrate that the examined IMU displayed promising capacity as a valid and reliability of the IMU, established through the successful completion of the aim and objective of this chapter, enabled these devices to be utilised as a tool for quantifying the frequency of technical actions performed during professional soccer training during experimental study two (Chapter 4), which is discussed further throughout Section 5.2.2.

The second experimental study conducted within this thesis (Chapter 4), aimed to quantify the within-microcycle, inter-positional, and between-drill differences in the frequency of technical actions performed during professional soccer training using foot-mounted IMUs. Although the frequency of

technical actions executed by professional players during match-play has risen over time (Barnes et al., 2014; Bush et al., 2015), these actions are consistently neglected by practitioners during player monitoring processes (Akenhead & Nassis, 2016; Malone et al., 2020), despite contributing to players' overall external training load (Bradley & Ade, 2018). Through the successful completion of the aforesaid aims and objectives, the novel data presented in Chapter 4 (discussed in detail in Section 5.2.2), has provided a broader understanding of the multidimensional periodisation strategies used to prepare professional players for competition, as well as the within-session distribution of technical actions.

#### 5.2. General Discussion of Findings

#### 5.2.1. Inertial Measurement Units

The first key finding of this research project was that the foot-mounted IMU examined during experimental study one (Chapter 3), exhibited consistently good concurrent validity for measuring the frequency of 8,640 ball touches ( $P_A = 95.1\% - 100.0\%$ ) and 5,760 releases ( $P_A = 95.1\% - 100.0\%$ ), collectively executed during a series of technical soccer tasks (Table 3.3). Having repeated each experimental trial three times, over two pre-determined distances of 13.2 m and 18.7 m (see Section 3.3.3.3 for a rationale), the foot-mounted IMU also displayed consistently good intra-unit reliability for measuring ball touches and releases, with respective  $P_A$  values ranging from 95.8% - 100.0% and 95.9% - 100.0%, respectively. Combined with the low CV values for ball touches (CV = 1.5% - 1.8%) and releases (CV = 1.4% - 2.9%), experimental study one concluded that the foot-mounted IMU displayed promising capacity as a valid and reliable method of quantifying technical actions performed during soccer training.

Wearable microtechnology is highly prevalent throughout professional soccer (Cummins et al., 2013; Bartlett et al., 2017), providing key stakeholders with an extensive volume of data pertaining to multiple performance variables (Coutts, 2014b). It has suggested that the most appropriate variables collected by MEMS directly relate to the competition demands of a particular sport (Impellizzeri et al., 2019). Therefore, the implementation of foot-mounted IMUs, that are capable of quantifying soccer-specific non-locomotor activity, may represent a timely addition to supplement the current player

monitoring procedures employed by professional soccer clubs (Lutz et al., 2020). This may be especially necessary in considering that practitioners often overlook metabolically demanding technical actions when planning training activities (Akenhead & Nassis, 2016; Malone et al., 2020). With technical actions such as ball touches and releases directly associated with the demands of professional soccer match-play (Buchheit & Simpson, 2017), and technical-related parameters considered a high priority by head coaches, especially during multicyclic in-season training phases (Morgans et al., 2014a), the ability to measure the frequency of these actions performed during training each day is advantageous.

Having established the validity and reliability of the foot-mounted IMUs (Chapter 3), the lack of which was labelled by 48 practitioners as a substantial barrier to the effective implementation of a new method of measuring player performance (Akenhead & Nassis, 2016), the wider considerations proposed by Starling and Lambert (2018) as prerequisites of an efficacious monitoring system can be considered. The application of foot-mounted IMUs satisfied several of these criteria; being noninvasive, non-fatiguing, and easy to administer. This method of measuring technical actions provides key stakeholders with objective feedback in a timely manner, whilst obliging a lesser financial commitment when compared with the previously discussed methods such as third-party data providers (Section 2.3.2) or semi-automatic multiple camera tracking systems (Section 2.3.3), which is especially desirable for EFL clubs competing below the top division of English soccer.

#### 5.2.2. Technical Actions During Professional Soccer Training

#### 5.2.2.1. Within-Microcycle Differences

This research project revealed that the frequency of technical actions performed during a typical weekly training microcycle peaked on the day immediately preceding competition (Table 4.2). This contradicted the body of previous research that has examined external training load throughout professional soccer training microcycles, which has consistently demonstrated a reduction in specific markers (e.g., total distance, mean speed) on MD - 1 (Anderson et al., 2015; Malone et al., 2015; Stevens et al., 2017; Martín-García et al., 2018). For example, Malone et al. (2015), reported a significant decrease in the total distance ( $\overline{X}^{diff}$  = -2,116.0 m, ES = 1.38, large) and high-speed running distance ( $\overline{X}^{diff}$ 

= -135.0 m, ES = 1.10, moderate) covered by EPL players on MD - 1 in comparison with MD - 5, with Martín-García et al. (2018) observing reductions between MD - 5 and MD - 1 in the same external training load variables (total distance:  $\overline{X}^{diff}$  = -1,851.0 m,  $p \le 0.005$ ; high-speed running distance:  $\overline{X}^{diff}$  = -66.0 m,  $p \le 0.005$ ). During experimental study two (Chapter 4), it would appear that practitioners promoted this pre-match physical taper (Malone et al., 2015; Owen et al., 2017) by prescribing a greater weighted percentage of position specific ( $\%^{diff}$  = 59.9), tactical ( $\%^{diff}$  = 91.7) and warm-up ( $\%^{diff}$  = 119.7) drills on this day (Table 4.5). This begins to provide empirical evidence to support the anecdotal notion that training objectives become more technical and tactical in nature as competition approaches (Martín-García et al., 2018; Walker & Hawkins, 2018).

Barrett and colleagues (2020) demonstrated that position specific ( $\overline{X}^{\text{diff}} = -602.0 \text{ m}, p \le 0.001$ ) and tactical ( $\overline{X}^{\text{diff}}$  = -98.0 m,  $p \le 0.001$ ) drills elicit a significantly lower total distance per minute than SSG, the largest weighted percentage of which during the current thesis was observed on MD - 1 (Table 4.5). Experimental study two (Chapter 4) revealed that training sessions on this day evoked almost four times the frequency of ball touches ( $\overline{X} = 218.0$ ), and more than double the frequency of releases ( $\overline{X} = 218.0$ ) 110.8), compared to previously reported match-play data from semi-automatic multiple camera tracking systems (Table 2.4) (Yi et al., 2020). This questions whether players' holistic readiness for the imminent fixture may have been unwittingly jeopardised (Anderson et al., 2016; Kelly et al., 2020), given the potential onset of neuromuscular residual fatigue attributed to the heightened frequency of technical actions performed (Guex & Millet, 2013, Silva et al., 2018). As noted in Section 2.2.2, the repeated eccentric contractions, and rapid eccentric-to-concentric transfer, required during kicking promotes structural muscular damage and inflammation (Guex & Millet, 2013), with numerous studies demonstrating the impact of lower-limb fatigue upon muscular strength, injury risk, and indices of technical performance (Apriantono et al., 2006; Kellis et al., 2006; Krustrup et al., 2010). Below, Figure 5.1 (Phase 1) depicts the backswing phase of a soccer kick, which requires a high-force eccentric contraction of the knee extensors (Brophy et el., 2007) to decelerate knee flexion and initiate the forward swing phase (Orchard et al., 1999). During the forward swing phase (Phase 2; Figure 5.1), the knee flexors contract eccentrically to prevent hyperextension of the knee joint (Dörge et al., 2002). However,

the residual fatigue induced by the increased eccentric activity (Proske & Morgan, 2001) during training on MD - 1 may inhibit this protective mechanism (Apriantono et al., 2006), potentially increasing players' susceptibility to kicking-related hamstring and groin injuries during an ensuing fixture (Andersen, 2014; Hölmich et al., 2014). From a performance perspective, Russell et al. (2011), concluded that neuromuscular fatigue impaired players' shooting accuracy (%<sup>diff</sup> = -25.5, *p* = 0.035) and passing speed ( $\overline{X}^{diff}$  = 0.8 m·s<sup>-1</sup>, *p* = 0.039), with Stone and Oliver (2009) demonstrating the significant impact of neuromuscular fatigue upon players' dribbling time (%<sup>inc</sup> = 4.5, *p* = 0.009) and shooting accuracy ( $\overline{X}^{diff}$  = -7.6 au, *p* = 0.012), during simulated soccer match-play. With laboratory and field-based soccer simulation protocols being validated for replicating multiple performance metrics during match-play (Stone et al., 2011; Robineau et al., 2012; Page et al., 2015), it could be suggested that the residual neuromuscular fatigue promoted by the heightened frequency of technical actions being observed on MD - 1 possesses the potential to impair players' technical performance during the forthcoming fixture.





Much of the published literature documenting the incidence of technical actions performed during professional soccer match-play (as discussed in Section 2.2, and displayed by Table 2.1, Table 2.2, Table 2.3 and Table 2.4) has quantified the whole match frequency of these actions (Taylor et al., 2017). Although such studies (e.g., Dellal et al., 2011a; Liu et al., 2016; Yi et al., 2019; 2020) provide meaningful insights into the overall volume of activity, solely reporting whole match demands fails to appropriately represent the intensity of these activities (Delaney et al., 2015; Lacome et al., 2016). Previous research examining more than 300 professional soccer matches has revealed that, for various reasons (e.g., injuries, substitutions), the ball goes out of play for a mean of 32.5 minutes (Hill-Haas et al., 2011; Martinez-Lagunas et al., 2014). Practitioners who fail to discount this period when interpreting players' external training load data risk underestimating the overall competition demands that soccer players must contend with (Wass et al., 2020). Therefore, reporting the frequency of technical actions as a function of ball-in-play time provides a superior representation of the intensity of players' activities (Pollard et al., 2018).

The notion of ball-in-play time during competition is directly transferrable to the training environment, where players may momentarily cease activity to rest, transition between drills, or receive instruction (Ford et al., 2010). The findings of experimental study two (Chapter 4) unveiled that, relative to ball-in-play time ( $\overline{X}$  = 41.5 min), training sessions on MD - 5 elicited the most ball touches per minute and releases per minute (Table 4.2). One plausible reason for this may relate to the nature of training activities delivered on this day, which saw the greatest proportion of technical drills compared with all other training days within a typical microcycle (Table 4.5). Although experimental study two failed to consider levels of match participation, which has demonstrated large (ES = 2.00 - 2.50) effects on indices of external training load (Anderson et al., 2015), the training group on MD - 5 often comprised non-starting and fringe players, with those who started the previous fixture taking part in recovery activities (Morgans et al., 2014a; Anderson et al., 2016). Practitioners frequently prescribe top-up training immediately after a fixture to compensate for the insufficient external training load encountered by partial-match and unused substitute players (Hills et al., 2018; Buchheit, 2019; Buckthorpe et al., 2019). However, such activities are solely physical in nature, with players scarcely prescribed supplementary technical activities (Hills et al., 2020a). This may be due to the FA's pitch protection regulations which permit only 15 minutes of post-match activity (Rule 23.11i, FA, 2020b), team travel requirements (i.e., the return journey from a lengthy away fixture) (Hills et al., 2020a), or a lack of available coaching staff (i.e., due to post-match media obligations) (Hills et al., 2020b). Subsequently, it would appear that practitioners attempt to limit the consequences of reversibility (Farrow & Robertson, 2017), by utilising technical drills on MD - 5 to provide non-starting and fringe players with sufficient perceptual-cognitive stimuli that is crucial for technical performance (Reilly et al., 2000; Williams & Hodges, 2005; Guilherme et al., 2015).

## 5.2.2.2. Inter-Positional Differences

Experimental study two (Chapter 4), revealed trivial-to-moderate (ES = 0.01 - 0.64) inter-positional differences in the technical actions of professional soccer training, with CM performing the most absolute and relative ball touches and releases during a typical training session (Table 4.3). This implies that the frequency of technical actions executed by players who occupy this position during training are partially specific to those experienced during competition (Farrow & Robertson, 2017), as previously reported match-play data from semi-automatic multiple camera tracking systems has indicated that this position typically performs the most ball touches ( $\overline{X} = 67.9 \pm 23.2$ ) and releases ( $\overline{X} = 57.9 \pm 29.5$ ) per match (Table 2.4) (Yi et al., 2020). This is likely related to the tactical responsibilities of CM (Dellal et al., 2011a), which primarily involves coordinating attacking play and creating goal scoring opportunities for their teammates (Gonçalves et al., 2014; Bush et al., 2015). For instance, regardless of match status (i.e., winning, drawing, or losing), 61.0% of passes originate from the midfield third of the pitch (Taylor et al., 2010). Moreover, previous research has indicated that the technical actions performed by CM during match-play are stable, despite the potential influence of situational variables (as discussed in Section 2.2.1). Specifically, Yi et al. (2020), reported trivial differences between the frequency of technical actions when playing at home versus playing away, as well as trivial differences when playing against a higher quality of opposition. This emphasises the importance of the training activities prescribed to CM being specific to the requirements encountered during match-play (Farrow & Robertson, 2017), given the apparent stability of the technical actions performed by this position during competition.

The lowest frequency of ball touches and releases, and the lowest relative frequency of ball touches per minute and releases per minute, was observed within ST (Table 4.3). Given that ST execute the fewest ball touches ( $\overline{X} = 52.1 \pm 20.3$ ) and releases ( $\overline{X} = 41.0 \pm 22.7$ ) during competition (Table 2.4) (Yi et al., 2020), the notion of specificity would advocate the lowest frequency of technical actions being performed by this position during training (Farrow & Robertson, 2017). However, in considering the crucial primary tactical role played by ST during competition (i.e., to score goals) (Hughes et al., 2012), the fact that players who occupy this position executed the fewest releases during training may be considered surprising. For example, 16.1% of all final third entries in English professional soccer end with a shot, with only 8.9% resulting in a shot on target (Kite & Nevill, 2017). Performing one additional shot on target per match would increase a team's probability of winning by 12.4% (Kite & Nevill, 2017), with the mean shot conversion rate throughout the EFL being just  $8.2\% \pm 10.3\%$  during the 2019/2020 season (OPTA Sports, 2020). With ST executing the most shots during competition (Table 2.4, Yi et al., 2020), and these opportunities being relatively rare (Kite & Nevill, 2017), the principle of progression proposes that ST should increase the frequency of releases performed during training. Engaging in more deliberate practice should, theoretically, result in measurable changes in technical proficiency (Ericsson et al., 1993; Farrow & Robertson, 2017). However, coach interventions should employ a differential learning approach (Savelsbergh et al., 2010) to vary the manner in which the skill of shooting is practiced (i.e., kicking a moving ball, combinations with other players, different zones within the goal to hit) (Schöllhorn et al., 2006), thereby preventing tedium by reducing monotony (Farrow & Robertson, 2017). This, in turn, should enhance player adherence and intervention outcome success (Soligard et al., 2010; Steffen et al., 2013).

#### 5.2.2.3 Between-Drill Differences

Each of the 7,739 individual drill observations ascertained throughout the 24-weekly training microcycles (Figure 4.1) was assigned to one of six distinct categories according to their primary objective (Table 4.1). Subsequently, drill category displayed trivial-to-very large (ES = 0.04 - 3.04) effects on the relative frequency of ball touches per minute and releases per minute performed during training (Table 4.4).

One drill that is routinely employed in professional soccer training is SSG (Hill-Hass et al., 2011), thought to simultaneously provide players with similar technical, tactical, physiological, and psychological stimuli to that encountered during match-play (Halouani et al., 2014; Bujalance-Moreno et al., 2019). The time-efficient multifaceted nature of SSG makes this type of drill particularly useful at the elite level, where training time is limited due to congested fixture schedules (Morgans et al., 2014b). Indeed, SSG were the most prevalent training drill observed during experimental study two (Chapter 4), accounting for 49.5% (n = 3,831) of the total number of individual drill observations, with the highest proportion being observed on MD - 1 (Table 4.5). However, the frequency of ball touches per minute and releases per minute elicited by this training modality exhibited only trivial-to-small (ES = 0.00 - 0.35) differences according to playing position (Figure 4.5). This begins to question whether the specificity of SSG for replicating the distinct inter-positional technical requirements of match-play may be limited (Farrow & Robertson, 2017). The only non-trivial differences during SSG were observed within CM, who executed more ball touches per minute than CD ( $\overline{X}^{diff} = 0.5$ , ES = 0.25, small) and ST ( $\overline{X}^{\text{diff}} = 0.7$ , ES = 0.35, small). However, for all playing positions, SSG evoked a higher frequency of ball touches per minute ( $\overline{X}^{\text{diff}} = 1.5$ ) and releases per minute ( $\overline{X}^{\text{diff}} = 0.3$ ) than previously reported match-play data (Yi et al., 2020). This elevated relative frequency of technical actions performed, alongside the concurrent perceptual-cognitive demands of these drills (Sampaio & Maçãs, 2012; Aguiar et al., 2015), suggests that SSG may provide practitioners with an efficacious training modality for facilitating the principles of progression and overload (Farrow & Robertson, 2017).

Notwithstanding the influence of playing position, the lowest frequency of ball touches per minute and releases per minute was observed during tactical drills (Table 4.4). With players' tactical roles being a powerful determinant of match performance (Bradley & Ade, 2018), tactical drills (e.g., team shape, patterns of play, set pieces) are arguably the most important training exercises that professional soccer players are exposed to. However, tactical drills provided professional soccer players with a lower relative technical stimulus than any other drill category, likely attributed to their intermittent nature (Siegle & Lames, 2012). For example, analysis of coach behaviours when delivering playing form (i.e., tactical) drills to elite soccer players has revealed that these drills incur frequent

interruptions to provide instruction ( $\overline{X} = 1.8 \cdot \min^{-1}$ ) and management-related ( $\overline{X} = 1.3 \cdot \min^{-1}$ ) information (Ford et al., 2010). Although instruction and management are crucial for delivering tactical messages (Cushion & Jones, 2001), which are especially important during periods of fixture congestion, previous research has demonstrated the potential issues related to interrupting training activities too frequently (Williams & Hodges, 2005). Therefore, practitioners may wish to adopt a less prescriptive approach during tactical drills to facilitate guided discovery (Smeeton et al., 2005; Partington & Cushion, 2013; O'Connor et al., 2017) and, subsequently, avert tedium during these activities (Farrow & Robertson, 2017).

#### 5.3. Limitations

Although the aims and objectives of this research project have been achieved (Section 5.1.1), each experimental study conducted within this thesis is not without limitation. Therefore, the following section shall outline the limitations encountered during both experimental study one (Chapter 3) and experimental study two (Chapter 4), before Section 5.4 provides directions for future research which seek to alleviate these limitations.

Experimental study one (Chapter 3), quantified the concurrent validity and intra-unit reliability of a foot-mounted IMU throughout a series of rudimentary open skill soccer activities (Singer, 2000). The amateur soccer players were required to execute controlled, discrete, technical soccer tasks that are commonly observed during training sessions which, other than responding to a predictable incoming ball from their partner, required little perceptual-cognitive proficiency (Williams, 2000). These training form tasks were specified to diminish the potential for human error impacting the data gathered by the IMU, given that there have been no previous scholarly examinations of the technical-related capabilities of the device. Whilst providing an essential reference point that future research may seek to build upon, the validity and reliability of the IMUs is yet to be comprehensively examined during soccer tasks of increasing complexity, such as SSG or match-play. As these playing form activities are more representative of competitive scenarios (Ford et al., 2010), which may involve instances of foot-to-foot contact between opponents contesting for ball possession, it is conceivable that the IMUs may incorrectly record such instances as false-positive ball touches and releases, thereby decreasing the concurrent validity and/or intra-unit reliability of the devices during these scenarios (Figure 2.5). In considering the prevalence of SSG throughout professional soccer training regimes, as displayed by Table 4.5 and previously demonstrated by Barrett et al. (2020), an IMU that falsely overestimates the frequency of technical actions performed may be problematic for abiding by the principles of skill acquisition periodisation (Farrow & Robertson, 2017). For instance, practitioners seeking to promote the principle of progression, by prescribing opposed training drills that require a greater frequency of technical actions than that observed during competition (as discussed in Section 2.4.3), risk making performance-related decisions upon data that may contain inaccuracies. This limitation directly relates to the first direction for future research, which is discussed in the following section.

Experimental study two (Chapter 4), utilised the foot-mounted IMU to quantify the withinmicrocycle, inter-positional, and between-drill differences in the frequency of ball touches, releases, ball touches per minute, and releases per minute performed during professional soccer training. Despite providing an automated alternative method to manual coding players' technical actions (see Section 2.3.1), the foot-mounted IMU failed to match the rich detail provided by human performance analysts. For example, the device was only capable of quantifying the 'who?' (i.e., the specific player) and the 'what?' (i.e., ball touch, release), whereas manual coding enables additional parameters such as the 'where?' (i.e., the location on the pitch that the action occurred) and 'when?' (i.e., the time during an activity that the action took place) to be established (Kipling, 1902). Furthermore, the term 'releases' (operationally defined in Table 3.2), which was adapted from the term 'distributions' previously applied within the literature, enumerated the cumulative total number of passes, crosses, shots, and clearances performed (Russell et al., 2013; Harper et al., 2014). As such, the device was unable to differentiate between the specific types of release performed, with one recorded release potentially being a pass, cross, shot, or clearance. Consequently, head coaches and practitioners receive less objective information upon which to make informed decisions regarding the nature of training activities or team preparation (O'Donoghue, 2007). Such information may have the potential to assist head coaches who are planning to execute a specific tactical strategy during a forthcoming fixture, such as placing emphasis on players' crossing ability when preparing to exploit an opponent who may have conceded a high number of goals from these scenarios.

The inability of the foot-mounted IMU to quantify the specific types of release executed may further limit the subsequent usefulness of the monitoring system, given that each type may possess distinct metabolic requirements (Osgnach et al., 2010; Walker et al., 2016). For example, a player's shank angular velocity when executing a simple pass to a teammate who is within close proximity (i.e., a lateral pass between two CD) is likely to be lower than when a player is making a defensive clearance or taking a shot towards goal. Without distinguishing between the specific types of release performed, practitioners are restricted to making relatively simple interpretations based on the IMU data from each training session, such as making between-player comparisons in the frequency of ball touches and releases executed. However, whilst hypothetical Player A may have performed a lower frequency (i.e., volume) of releases than hypothetical Player B, the velocity (i.e., intensity) of these actions performed by Player A may be consistently higher, culminating in this player encountering a greater metabolic cost than Player B. Examining the shank angular velocity of each release may, therefore, provide an understanding of the resulting biomechanical load imposed on the musculoskeletal system (Vanrenterghem et al., 2017), which would enhance practitioners' ability to gauge players' holistic readiness to perform in conjunction with current monitoring systems (Bradley & Ade, 2018; Verheul et al., 2020).

Another limitation encountered during experimental study two (Chapter 4), was the requirement to compare the frequency of technical actions performed during training, as measured by foot-mounted IMUs, with the frequency of these actions executed during match-play derived from semi-automatic multiple camera tracking systems (see Section 2.3.3). Although previous research has emphasised caution when comparing data from different player monitoring systems (Taberner et al., 2020), due to potential differences in operational definitions, sampling rate, and/or data processing methods contributing to between-system discrepancies (Buchheit et al., 2014b), the foot-mounted IMU was not permitted for use during match-play under the Laws of the Game (Law 4.4; IFAB, 2020) at the time of writing. Therefore, to enable the frequency of technical actions performed by players during training to be compared with match-play, and to calculate players' cumulative weekly technical load (Taberner et al., 2020), practitioners are currently left with no choice but to utilise the data gathered by foot-mounted IMUs during training in conjunction with that obtained through semi-automatic multiple

camera tracking systems during match-play. The realisation of this limitation identified an important avenue that future research should explore, which is to be discussed shortly.

Experimental study two (Chapter 4) adopted a case-study approach, using data from only one soccer club, to achieve the aims and objectives of this thesis and provide a snapshot of the withinmicrocycle, inter-positional, and between-drill differences in the technical actions performed during professional soccer training. Although this approach is commonplace throughout the literature (e.g., Anderson et al., 2015; Malone et al., 2015; Stevens et al., 2017; Martín-García et al., 2018), there remains considerable debate regarding whether the conclusions drawn through utilising a case-study approach are broadly generalisable to wider populations (Potrac et al., 2014; Booroff et al., 2016). The stringent exclusion criteria (Figure 4.2) yielded a sample of 21 players which, when considered in relation to the 128,983 registered professional soccer players worldwide (FIFA, 2019b), represents a microscopic fragment of professional soccer training regimes as a whole (Greig & Walker-Johnson, 2007; Stodter & Cushion, 2019; Nosek et al., 2021). Moreover, the sample population was not random (Dalton-Barron et al., 2020), but rather one of convenience to the researcher (Francis & Jones, 2014; Akenhead & Nassis, 2016). The presence of specific idiosyncrasies at individual soccer clubs, such as the tactical systems (Whitehead et al., 2018) and within-microcycle schedules (Malone et al., 2015) employed by head coaches, are characteristic of each sampled team. Therefore, generalisability beyond the period within which players' data was collected is limited (Taylor et al., 2010; Fradua et al., 2013). Scholars have encouraged practitioners to exercise caution when seeking to extrapolate the conclusions of case study-based research (Ruiz-Ruiz et al., 2011; Tenga et al., 2010), beyond each respective soccer club (Collet, 2013), until data from a greater breadth of clubs is available (Bradley et al., 2013; Harrop & Nevill, 2014).

Whilst outside of the scope of the current thesis, the final limitation of experimental study two (Chapter 4) relates to the lack of consideration given to the various modifiable and non-modifiable situational variables (as discussed in Section 2.2.1), that may influence the structure, content, and delivery of professional soccer training activities. As alluded to, it is plausible that different levels of match participation may result in players executing varying frequencies of technical actions during weekly training microcycles. For instance, Anderson and colleagues (2015), reported that training

sessions for non-starting players had a significantly longer duration (p = 0.003, ES = 2.4, very large), and elicited a significantly greater total distance (p = 0.003, ES = 2.3, very large), than those for starting players (i.e., who started greater than 60.0% of matches). Furthermore, variables such as the team's league position at the time of a particular training session, weather conditions (Rein & Memmert, 2016), the nature of competition that players are preparing for (e.g., league, cup) (Taylor et al., 2010), or the type (e.g., artificial/natural grass) and condition of the playing surface (Andersson et al., 2008), has the potential to influence the nature of training activities prescribed. As aforementioned (see Section 2.2.1), technical performance profiles that fail to account for extraneous variables risk providing a superficial understanding of player performance (Paul et al., 2015; Trewin et al., 2017). This shortcoming can be alleviated through future research exploring the suggestions outlined in the next section.

### 5.4. Directions for Future Research

The previous section demonstrated the numerous drawbacks encountered throughout each experimental study conducted within the current thesis. The purpose of this section is to identify several avenues that forthcoming research might seek to explore in order to address these limitations.

Future research should endeavour to comprehensively scrutinise of the validity and reliability of the foot-mounted IMU used to establish the within-microcycle, inter-positional, and between-drill differences in the frequency of technical actions performed during professional soccer training. Although experimental study one (Chapter 3) provided a necessary introductory understanding of the efficacy of the IMUs, which had not been independently established prior to the commencement of this research project, an extensive exploration of the validity and reliability of these device during soccer tasks of incrementally increasing difficulty is warranted. For instance, the method of establishing the agreement between the foot-mounted IMU and retrospective video analyses during experimental study one (as described in Section 3.3.5) (Cooper et al., 2007), may be replicated within technical drills, SSG, and match-play, to establish whether the efficacy of the devices decreases within these progressively complex scenarios whereby the volume and/or intensity of players' technical actions may be heightened.

Given that experimental study two (Chapter 4) did not account for players' shank angular velocity during kicking, which would help practitioners to surmise the biomechanical load inflicted upon the musculoskeletal system as a result of performing technical actions (Vanrenterghem et al., 2017), it would be beneficial for ensuing research to develop an arbitrary measure of technical load. A cumulative vector magnitude index similar to Catapult's PlayerLoad<sup>™</sup> (Boyd et al., 2013; Barrett et al., 2016; Bray et al., 2016), which considers the shank angular velocity of each specific type of release performed (Lees et al., 2010), may provide a useful arbitrary value representative of the metabolic cost of players' technical performance (Boyd et al., 2013; Barrett et al., 2016; Dalen et al., 2016). This may enhance practitioners' ability to gauge players' holistic readiness to perform, in conjunction with the player monitoring systems currently implemented (Bradley & Ade, 2018; Verheul et al., 2020), or whether additional pre-competition recovery strategies (e.g., cold water immersion, compression garments) may be necessary (Cross et al., 2019; Altarriba-Bartes et al., 2020; Field et al., 2021).

As referred to in the previous section, the Laws of the Game (IFAB, 2020) prevented the footmounted IMU from being used during official competition match-play. Upon receiving the required FIFA International Match Standard certification (as discussed in Section 2.3.4.3), future research should establish the agreement between the IMUs and semi-automatic multiple camera tracking systems during professional soccer match-play. The interchangeability of player monitoring systems is a pertinent consideration, with it being customary for practitioners to use two methods of quantifying players' external load to be used simultaneously (i.e., one method during training and a different method during competition) (Taberner et al., 2020). A subsequent examination of the between-system TEM would enable researchers to develop calibration equations that facilitate the interchangeable use of different player monitoring systems in different environments (Buchheit et al., 2014b), thereby reducing the potential for inaccuracies when interpreting players' cumulative within-microcycle performance data.

The final line of enquiry that prospective research might examine relates to the restricted generalisability of the conclusions drawn from investigations that follow a case-study approach (Ruiz-Ruiz et al., 2011; Tenga et al., 2010; Bradley et al., 2013; Collet, 2013; Harrop & Nevill, 2014, Potrac et al., 2014; Booroff et al., 2016). It would be interesting to ascertain whether the trends and patterns identified during experimental study two (Chapter 4) are present when examining soccer clubs who

compete in different domestic league competitions. Despite the sociocultural consistencies present throughout professional soccer in England (Sapp et al., 2018), the nature of training activities prescribed to technically superior EPL players is likely to differ from those delivered at EFL League Two clubs, which may influence the frequency of technical actions executed during each training microcycle. As such, a large-scale investigation that repeats the methodology of experimental study two (Section 4.3) within multiple soccer clubs, who compete in alternative domestic league competitions, would leave practitioners better placed to extrapolate the findings of the current thesis to a wider breadth of populations.

A coordinated investigation, which examines the training procedures of clubs from the aforesaid four prominent European competitions (Section 2.2), whose historical socioeconomic idiosyncrasies are likely to affect training procedures (Sarmento et al., 2013; Sapp et al., 2018), would yield a broad understanding of the technical actions performed by a comprehensive sample of professional soccer players across the continent. Examining alternative competitions (

League of Ireland Premier Division), which have a within-season period spanning different calendar months (i.e., February to October; FIFA, 2019b) to the EFL Championship club examined during the current thesis (Section 4.3.1), may produce different conclusions to those presented by experimental study two (Section 4.4). As well as this, the frequency of technical actions executed by academy soccer players during training remains unexplored. Given that players within each developmental phase outlined by the Elite Player Performance Plan (EPPP) (EPL, 2011), likely possess distinct biological maturation characteristics (Lovell et al., 2015; Towlson et al., 2018; 2020; 2021), it is conceivable that the findings of the current thesis may of no use to practitioners working in academy soccer. Likewise, each phase of development has a specific focus, with the Foundation Phase "characterised by the development of individual technical skills and a specific focus on mastery of the ball" (EPL, 2011, p. 40), and the Youth Development Phase "increasing significantly in terms of the intensity of practice, frequency of games and the amount of time players spend with coaches at the club" (EPL, 2011, p. 41). Therefore, reproducing experimental study two (Chapter 4) within each developmental phase of a player's journey through the EPPP may be advantageous to those responsible for the appropriate holistic development of academy soccer players.

# **Chapter 6: Conclusion**

Having demonstrated the successful completion of the aims and objectives of the current research project, and situated the key findings presented throughout each experimental study in relation to previously published research, the following section provides a number of concluding remarks that summarise the contribution that this thesis has made to the field of sports science.

In conclusion, this research project typifies a novel methodology for measuring the frequency of technical actions performed during professional soccer using commercially available foot-mounted IMUs. Specifically, the IMU exhibited good concurrent validity ( $P_A = 95.1\% - 100.0\%$ ) and intra-unit reliability ( $P_A = 95.9\% - 96.9\%$ , CV = 1.4% - 2.9%) for measuring ball touches and releases throughout all experimental conditions. Such technological advancements, capable of quantifying sport-specific non-locomotor activities, have the potential to supplement current player monitoring procedures with the integration of technical performance data (Lutz et al., 2020; Malone et al., 2020). Given that technical actions are an important, yet commonly overlooked (Paul et al., 2015; Malone et al., 2020), component of external training load (Wallace et al., 2014; Scott et al., 2016a), and with technical-related parameters considered a high priority by head coaches during multicyclic in-season training phases (Morgans et al., 2014a), the ability to measure the frequency of these actions performed during training in a valid and reliable manner (Chapter 3) may be auspicious for players and practitioners alike.

Secondly, this project has advanced the evidence base that practitioners are able to refer to during their day-to-day working procedures, by revealing numerous within-microcycle, interpositional, and between-drill differences in the frequency of technical actions executed by professional soccer players during training. Explicitly, the most ball touches ( $\overline{X} = 218.0$ ) and releases ( $\overline{X} = 110.8$ ) were observed on MD - 1, with MD - 5 eliciting the highest frequency of ball touches per minute ( $\overline{X} = 3.8$ ) and releases per minute ( $\overline{X} = 1.7$ ). Central midfielders performed the most ball touches ( $\overline{X} = 221.9$ ), releases ( $\overline{X} = 108.3$ ), ball touches per minute ( $\overline{X} = 3.4$ ), and releases per minute ( $\overline{X} = 1.6$ ) during a typical training session. Small-sided games evoked more ball touches per minute ( $\overline{X}^{\text{diff}} = 1.5$ ), and releases per minute ( $\overline{X} = 1.2$ ), and releases per minute ( $\overline{X} = 0.5$ ), were observed during tactical drills. For reasons explained throughout this thesis, the integration of soccer-specific technical parameters, as a facet of

players' external training load within a comprehensive periodisation plan (Wallace et al., 2014; Scott et al., 2016a), has previously been absent from the literature. Therefore, the findings of experimental study two (Chapter 4) contribute towards a unique understanding of the multidimensional periodisation strategies used to systematically manipulate players' external training load (Mujika et al., 2018), by expanding upon previous research that has exclusively focussed upon time-motion related parameters (Todd et al., 2012).

#### **6.1. Practical Applications**

In order to positively influence and advance contemporary practice, it is paramount that the fast working professional soccer practitioners are able to deduce meaningful information from the current thesis (Coutts, 2016). Therefore, this section outlines various implications that may be beneficial to those responsible for prescribing and monitoring training activities in professional soccer.

The foot-mounted IMU examined throughout this research project possessed promising capacity as a valid and reliable alternative method of quantifying soccer-specific technical actions. Implementation of foot-mounted IMUs may represent a timely addition to the player monitoring procedures currently employed by professional soccer clubs (Weston, 2018), potentially assisting practitioners in their injury risk modification strategies (Ehrmann et al., 2016), by enabling the formulation of players' normative technical performance profiles for each day within a microcycle (Akenhead & Nassis, 2016). This may be especially necessary in considering that practitioners repeatedly overlook metabolically demanding technical actions when devising training activities (Malone et al., 2020).

Given that training activities become more technically and tactically oriented as competition approaches (Martín-García et al, 2018; Walker & Hawkins, 2018), contributing to the frequency of technical actions executed by professional soccer players peaking on the day immediately preceding a fixture (Table 4.2), the insights provided by this investigation have the potential to inform precompetition recovery strategies to negate the neuromuscular fatigue possibly induced through increased technical activity on MD - 1 (Rey et al., 2012a; 2012b; Nédélec et al., 2015a).

Finally, the ability to quantify technical actions in the training environment may equip practitioners with the capacity to tailor training activities according to the principles of skill acquisition periodisation (Farrow & Robertson, 2017; Mujika et al., 2018). Longitudinal adherence to this framework should contribute to players experiencing sustained skill-related performance enhancements which, ultimately, increase the likelihood of prolonged competition success.

## Chapter 7: References

Abade, E., Gonçalves, B., Leite, N. & Sampaio, J. (2014) Time-motion and physiological profile of football training sessions performed by under-15, under-17, and under-19 elite Portuguese players. *International Journal of Sports Physiology and Performance*, 9(3), 463-470.

Abbott, W., Brickley, G. & Smeeton, N. (2018) An individual approach to monitoring locomotive training load in English Premier League academy soccer players. *International Journal of Sports Science and Coaching*, 13(3), 421-428.

Abrantes, C., Nunes, M., Maçãs, V., Leite, N. & Sampaio, J. (2012) Effects of the number of players and game type constrains on heart rate, rating of perceived exertion, and technical actions of small-sided soccer games. *The Journal of Strength andConditioning Research*, 26(4), 976-981.

Abt, G. & Lovell, R. (2009) The use of individualised speed and intensity thresholds for determining the distance run at high-intensity in professional soccer. *Journal of Sports Sciences*, 27(9), 893-898.

Ade, J., Fitzpatrick, J. & Bradley, P. (2016) High-intensity efforts in elite soccer matches and associated movement patterns, technical skills and tactical actions. Information for position-specific training drills. *Journal of Sports Sciences*, 34(24), 2205-2214.

Aguiar, M., Botelho, G., Gonçalves, B. & Sampaio, J. (2013) Physiological responses and activity profiles of football small-sided games. *The Journal of Strength and Conditioning Research*, 27(5), 1287-1294.

Aguiar, M., Gonçalves, B., Botelho, G., Lemmink, K. & Sampaio, J. (2015) Footballers' movement behaviour during 2-, 3-, 4- and 5-a-side small-sided games. *Journal of Sports Sciences*, 33(12), 1259-1266.

Ahmadi, A., Rowlands, D. & James, D. (2009) Towards a wearable device for skill assessment and skill acquisition of a tennis player during the first serve. *Sports Technology*, 2(3-4), 129-136.

Akenhead, R. & Nassis, G. (2016) Training load and player monitoring in high-level football: current practice and perceptions. *International Journal of Sports Physiology and Performance*, 11(5), 587-593. Akenhead, R., Harley, J. & Tweddle. S. (2016) Examining the external load of an English Premier League football team with special reference to acceleration. *Journal of Strength and Conditioning Research*, 30(9), 2424-2432.

Alberti, G., Iaia, F., Arcelli, E., Cavaggioni, L. & Rampinini, E. (2013) Goal scoring patterns in major European soccer leagues. *Sports Sciences for Health*, 9(3), 151-153.

Alexiou, H. & Coutts, A. (2008) A comparison of methods used for quantifying internal training load in women soccer players. *International Journal of Sports Physiology and Performance*, 3(3), 320-330. Ali, A. (2011) Measuring soccer skill performance: a review. *Scandinavian Journal of Medicine and Science in Sports*, 21(2), 170-183.

Ali, A., Williams, C., Hulse, M., Strudwick, A., Reddin, J., Howarth, L., Eldred, J., Hirst, M. & McGregor, S. (2007) Reliability and validity of two tests of soccer skill. *Journal of Sports Sciences*, 25(13), 1461-1470.

Altarriba-Bartes, A., Peña, J., Vicens-Bordas, J., Milà-Villaroel, R. & Calleja-González, J. (2020) Postcompetition recovery strategies in elite male soccer players. Effect on performance: a systematic review and meta-analysis. *PloS One*, 15(10), 1-20.

Altman, D. (1991) Practical statistics for medical research. London: Chapman & Hall.

Andersen, L. (2014) Risk factors for groin injury during football kicking. *ASPETAR Sport Medicine Journal*, 3(4), 252-256.

Anderson, L., Orme, P., Di Michele, R., Close, G., Milsom, J., Morgans, R., Drust, B. & Morton, J. (2015) Quantification of season-long physical load in soccer players with different starting status from the English Premier League: implications for maintaining squad physical fitness. *International Journal of Sports Physiology and Performance*, 11(8), 1038-1046.

Anderson, L., Orme, P., Di Michele, R., Close, G., Morgans, R., Drust, B. & Morton, J. (2016) Quantification of training load during one-, two- and three-game week schedules in professional soccer players from the English Premier League: implications for carbohydrate periodisation. *Journal of Sports Sciences*, 34(13), 1250-1259.

Andersson, H., Ekblom, B. & Krustrup, P. (2008) Elite football on artificial turf versus natural grass: movement patterns, technical standards, and player impressions. *Journal of Sports Sciences*, 26(2), 113-122.

Apriantono, T., Nunome, H., Ikegami, Y. & Sano, S. (2006) The effect of muscle fatigue on instep kicking kinetics and kinematics in association football. *Journal of Sports Sciences*, 24(9), 951-960.

Aquino, R., Puggina, E., Alves, I. & Garganta, J. (2017) Skill-related performance in soccer: a systematic review. *Human Movement*, 18(5), 3-24.

Araújo, D., Davids, K. & Hristovski, R. (2006) The ecological dynamics of decision making in sport. *Psychology of Sport and Exercise*, 7(6), 653-676.

Argote, L. & Ingram, P. (2000) Knowledge transfer: a basis for competitive advantage in firms. *Organisational Behaviour and Human Decision Processes*, 82(1), 150-169.

Atkinson, G. & Nevill, A. (1998) Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Medicine*, 26(4), 217-238.

Balyi, I. & Hamilton, A. (2004) Long-term athlete development: trainability in childhood and adolescence. *Olympic Coach*, 16(1), 4-9.

Bangsbo, J., Mohr, M. & Krustrup, P. (2006a) Physical and metabolic demands of training and matchplay in the elite football player. *Journal of Sports Sciences*, 24(7), 665-674.

Bangsbo, J., Mohr, M., Poulsen, A., Perez-Gomez, J. & Krustrup, P. (2006b) Training and testing the elite athlete. *Journal of Exercise Science and Fitness*, 4(1), 1-14.

Baptista, I., Johansen, D., Seabra, A. & Pettersen, S. (2018) Position specific player load during matchplay in a professional football club. *PloS One*, 13(5), 1-10.

Barfield, W., Kirkendall, D. & Yu, B. (2002) Kinematic instep kicking differences between elite female and male soccer players. *Journal of Sports Science and Medicine*, 1(3), 72-79.

Barnes, C., Archer, D., Bush, M., Hogg, B. & Bradley, P. (2014) The evolution of physical and technical performance parameters in the English Premier League. *International Journal of Sports Medicine*, 35(13), 1095-1100.

Barreiros, J., Figueiredo, T. & Godinho, M. (2007) The contextual interference effect in applied settings. *European Physical Education Review*, 13(2), 195-208.

Barrett, S. (2017) Monitoring elite soccer players' external loads using real-time data. *International Journal of Sports Physiology and Performance*, 12(10), 1285-1287.

Barrett, S., Midgley, A. & Lovell, R. (2014) PlayerLoad<sup>™</sup>: reliability, convergent validity, and influence of unit positioning during treadmill running. *International Journal of Sports Physiology and Performance*, 9(6), 945-952.

Barrett, S., Midgley, A., Reeves, M., Joel, T., Franklin, E., Heyworth, R., Garrett, A. & Lovell, R. (2016) The within-match patterns of locomotor efficiency during professional soccer match play: implications for injury risk? *Journal of Science and Medicine in Sport*, 19(10), 810-815.

Barrett, S., Varley, M., Hills, S., Russell, M., Reeves, M., Hearn, A. & Towlson, C. (2020) Understanding the influence of the head coach on soccer training drills: an eight-season analysis. *Applied Sciences*, 10(22), 8149-8162.

Bartlett, J. & Drust, B. (2020) A framework for effective knowledge translation and performance delivery of sports scientists in professional sport. *European Journal of Sports Science*, online ahead of print.

Bartlett, J., O'Connor, F., Pitchford, N., Torres-Ronda, L. & Robertson, S. (2017) Relationships between internal and external training load in team-sport athletes: evidence for an individualised approach. *International Journal of Sports Physiology and Performance*, 12(2), 230-234.

Bate, D. (1996) Soccer skills practice. In Reilly, T. (ed) *Science and soccer*. London: E. & F. N. Spon, 227-241.

Bateman, M. & Jones, G. (2019) Strategies for maintaining the coach-analyst relationship within professional football utilising the COMPASS model: the performance analyst's perspective. *Frontiers in Psychology*, 10(1), 2064-2076.

Bernstein, N. (1967) The coordination and regulations of movements. Oxford: Pergamon Press.

Bland, J. & Altman, D. (1986) Statistical methods for assessing agreement between two methods of clinical measurement. *The Lancet*, 327(8476), 307-310.

Bland, J. & Altman, D. (1999) Measuring agreement in method comparison studies. *Statistical Methods in Medical Research*, 8(2), 135-160.

Bompa, T. (1994) *Theory and methodology of training: the key to athletic performance*. Dubuque: Kendall Hunt Publishing Company.

Bompa, T. (1999) *Periodisation training: theory and methodology*. Champaign, Human Kinetics.Booroff, M., Nelson, L. & Potrac, P. (2016) A coach's political use of video-based feedback: a case study in elite-level academy soccer. *Journal of Sports Sciences*, 34(2), 116-124.

Borg, D., Nguyen, R. & Tierney, N. (2021) Missing data: current practice in football research and recommendations for improvement. *Science and Medicine in Football*, online ahead of print.

Bourdon, P., Cardinale, M., Murray, A., Gastin, P., Kellmann, M., Varley, M., Gabbett, T., Coutts, A., Burgess, D., Gregson, W. & Cable, N. (2017) Monitoring athlete training loads: consensus statement. *International Journal of Sports Physiology and Performance*, 12(2), 161-170.

Boyd, L., Ball, K. & Aughey, R. (2011) The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *International Journal of Sports Physiology and Performance*, 6(3), 311-321.

Boyd, L., Ball, K. & Aughey, R. (2013) Quantifying external load in Australian football matches and training using accelerometers. *International Journal of Sports Physiology and Performance*, 8(1), 44-51.

Bradley, P. & Ade, J. (2018) Are current physical match performance metrics in elite soccer fit for purpose or is the adoption of an integrated approach needed? *International Journal of Sports Physiology and Performance*, 13(5), 656-664.

Bradley, P. & Noakes, T. (2013) Match running performance fluctuations in elite soccer: indicative of fatigue, pacing or situational influences? *Journal of Sports Sciences*, 31(15), 1627-1638.

Bradley, P., Carling, C., Diaz, A., Hood, P., Barnes, C., Ade, J., Boddy, M., Krustrup, P. & Mohr, M. (2013) Match performance and physical capacity of players in the top three competitive standards of English professional soccer. *Human Movement Science*, 32(4), 808-821.

Bradley, P., Di Mascio, M., Peart, D., Olsen, P. & Sheldon, B. (2010) High-intensity activity profiles of elite soccer players at difference performance levels. *The Journal of Strength and Conditioning Research*, 24(9), 2343-2351.

Bradley, P., Lago-Peñas, C., Rey, E. & Sampaio, J. (2014) The influence of situational variables on ball possession in the English Premier League. *Journal of Sports Sciences*, 32(20), 1867-1873.

Bradley, P., O'Donoghue, P., Wooster, B. & Tordoff, P. (2007) The reliability of ProZone MatchViewer: a video-based technical performance analysis system. *International Journal of Performance Analysis in Sport*, 7(3), 117-129.

Brady, F. (1998) A theoretical and empirical review of the contextual interference effect and the learning of motor skills. *Quest*, 50(3), 266-293.

Brandes, M., Heitmann, A. & Müller, L. (2012) Physical responses of different small-sided game formats in elite youth soccer players. *The Journal of Strength and Conditioning Research*, 26(5), 1353-1360.

Bray, J., Fogarty, M., Barrett, S., Lovell, R. & Abt, G. (2016) Using microtechnology to evaluate the between- and within-match variability of professional Twenty20 cricket fast bowlers. *Professional Strength and Conditioning*, 43(1), 19-26.

Brink, M., Kuyvenhoven, J., Toering, T., Jordet, G. & Frencken, W. (2018) What do football coaches want from sport science? *Kinesiology*, 50(1), 150-154.

Brophy, R., Backus, S., Pansy, B., Lyman, S. & Williams, R. (2007) Lower extremity muscle activation and alignment during the soccer instep and side-foot kicks. *Journal of Orthopaedic and Sports Physical Therapy*, 37(5), 260-268.

Brophy, R., Silvers, H., Gonzales, T. & Mandelbaum, B. (2010) Gender influences: the role of leg dominance in ACL injury among soccer players. *British Journal of Sports Medicine*, 44(10), 694-697.
Buchheit, M. (2016) Chasing the 0.2. *International Journal of Sports Physiology and Performance*, 11(4), 417-418.

Buchheit, M. (2017a) Want to see my report, coach? Sport science reporting in the real world. *Aspetar Sports Medicine Journal*, 6(1), 36-43.

Buchheit, M. (2017b) Houston, we still have a problem. *International Journal of Sports Physiology and Performance*, 12(8), 1111-1114.

Buchheit, M. (2019) Managing high-speed running load in professional soccer players: the benefit of high-intensity training supplementation. *Sports Performance and Science Reports*, 53(1), 1-5.

Buchheit, M. & Simpson, B. (2017) Player tracking technology: half-full or half-empty glass? *International Journal of Sports Physiology and Performance*, 12(2), 35-41.

Buchheit, M., Al Haddad, H., Simpson, B., Palazzi, D., Bourdon, P., Di Salvo, V. & Mendez-Villanueva, A. (2014a) Monitoring accelerations with GPS in football: time to slow down? *International Journal of Sports Physiology and Performance*, 9(3), 442-445. Buchheit, M., Allen, A., Poon, T., Modonutti, M., Gregson, W. & Di Salvo, V. (2014b) Integrating different tracking systems in football: multiple camera semi-automatic system, local position measurement and GPS technologies. *Journal of Sports Sciences*, 32(20), 1844-1857.

Buckthorpe, M., Wright, S., Bruce-Low, S., Nanni, G., Sturdy, T., Gross, A., Bowen, L., Styles, B., Della Villa, S., Davison, M. & Gimpel, M. (2019) Recommendations for hamstring injury prevention in elite football: translating research into practice. *British Journal of Sports Medicine*, 53(7), 449-456. Bujalance-Moreno, P., Latorre-Román, P. & García-Pinillos, F. (2019) A systematic review on small-sided games in football players: acute and chronic adaptations. *Journal of Sports Sciences*, 37(8), 921-949.

Burgess, D. (2017) The research doesn't always apply: practical solutions to evidence-based trainingload monitoring in elite team sports. *International Journal of Sports Physiology and Performance*, 12(2), 136-141.

Bush, M., Barnes, C., Archer, D., Hogg, B. & Bradley, P. (2015) Evolution of match performance parameters for various playing positions in the English Premier League. *Human Movement Science*, 39(1), 1-11.

Butterworth, A., O'Donoghue, P. & Cropley, B. (2013) Performance profiling in sports coaching: a review. *International Journal of Performance Analysis in Sport*, 13(3), 572-593.

Calder, J. & Durbach, I. (2015) Decision support for evaluating player performance in rugby union. International Journal of Sports Science and Coaching, 10(1), 21-37.

Cardinale, M. & Varley, M. (2017) Wearable training-monitoring technology: applications, challenges, and opportunities. *International Journal of Sports Physiology and Performance*, 12(2), 55-62.

Carey, D., Smith, G., Smith, D., Shepherd, J., Skriver, J., Ord, L. & Rutland, A. (2001) Footedness in world soccer: an analysis of France '98. *Journal of Sports Sciences*, 19(11), 855-864.

Carling, C. (2013) Interpreting physical performance in soccer match-play: should we be more pragmatic in our approach? *Sports Medicine*, 43(8), 655-663.

Carling, C., Bloomfield, J., Nelsen, L. & Reilly, T. (2012) The role of motion analysis in elite soccer: contemporary performance measurement techniques and work rate data. *Sports Medicine*, 38(10), 839-862.
Carling, C., Bradley, P., McCall, A. & Dupont, G. (2016) Match-to-match variability in high-speed running activity in a professional soccer team. *Journal of Sports Sciences*, 34(24), 2215-2223.

Carling, C., Espié, V., Le Gall, F., Bloomfield, J. & Jullien, H. (2010) Work-rate of substitutes in elite soccer: a preliminary study. *Journal of Science and Medicine in Sport*, 13(2), 253-255.

Carling, C., Le Gall, F., McCall, A., Nédélec, M. and Dupont, G. (2015) Squad management, injury and match performance in a professional soccer team over a championship-winning season. *European Journal of Sport Sciences*, 15(7), 573-582.

Carling, C., Williams, A. & Reilly, T. (2005) *Handbook of soccer match analysis: a systematic approach to improving performance*. London: Routledge.

Carling, C., Wright, C., Nelson, L. & Bradley, P. (2014) Comment on 'Performance Analysis in football: a critical review and implications for future research'. *Journal of Sports Sciences*, 32(1), 2-7.

Carson, H. & Collins, D. (2011) Refining and regaining skills in fixation/diversification stage performers: the Five-A model. *International Review of Sport and Exercise Psychology*, 4(2), 146-167.

Casamichana, D. & Castellano, J. (2010) Time-motion, heart rate, perceptual and motor behaviour demands in small-sided soccer games. *Journal of Sports Sciences*, 28(14), 1615-1623.

Casamichana, D. & Castellano, J. (2015) The relationship between intensity indicators in small-sided soccer games. *Journal of Human Kinetics*, 46(1), 119-128.

Casamichana, D., Castellano, J., Calleja-Gonzalez, J., San Román, J. & Castagna, C. (2013) Relationship between indicators of training load in soccer players. *The Journal of Strength and Conditioning Research*, 27(2), 369-374.

Castellano, J., Alvarez-Pastor, D. & Bradley, P. (2014) Evaluation of research using computerised tracking systems (AMISCO<sup>®</sup> and ProZone<sup>®</sup>) to analyse physical performance in elite soccer: a systematic review. *Sports Medicine*, 44(5), 701-712.

Castellano, J., Casamichana, D. & Dellal. A. (2013) Influence of game format and number of players on heart rate responses and physical demands in small-sided soccer games. *The Journal of Strength and Conditioning Research*, 27(5), 1295-1303.

Castellano, J., Casamichana, D. & Lago, C. (2012) The use of match statistics that discriminate between successful and unsuccessful soccer teams. *Journal of Human Kinetics*, 31(1), 139-147.

Chambers, R., Gabbett, T., Cole, M. & Beard, A. (2015) The use of wearable microsensors to quantify sport-specific movements. *Sports Medicine*, 45(7), 1065-1081.

Champ, F., Ronkainen, N., Nesti, M., Tod, D. & Littlewood, M. (2020) 'Through the lens of ethnography': perceptions, challenges, and experiences of an early career practitioner-researcher in professional football. *Qualitative Research in Sport, Exercise and Health*, 12(4), 513-529.

Chardonnens, J., Favre, J., Cuendet, F., Gremion, G. & Aminian, K. (2013) Characterisation of lowerlimbs inter-segment coordination during the take-off extension in ski jumping. *Human Movement Science*, 32(4), 741-752.

Chardonnens, J., Favre, J., Le Cellennec, B., Cuendet, F., Gremion, G. & Aminian, K. (2012) Automatic measurement of key ski jumping phases and temporal events with a wearable system. *Journal of Sports Sciences*, 30(1), 53-61.

Chmura, P., Andrzejewski, M., Konefał, M., Mroczek, D., Rokita, A. & Chmura, J. (2017) Analysis of motor activities of professional soccer players during the 2014 World Cup in Brazil. *Journal of Human Kinetics*, 56(1), 187-195.

Colby, M., Dawson, B., Heasman, J., Rogalski, B. & Gabbett, T. (2014) Accelerometer and GPSderived running loads and injury risk in elite Australian footballers. *The Journal of Strength and Conditioning Research*, 28(8), 2244-2252.

Colby, M., Dawson, B., Peeling, P., Heasman, J., Rogalski, B., Drew, M. & Stares, J. (2018) Improvement of prediction of noncontact injury in elite Australian footballers with repeated exposure to established high-risk workload scenarios. *International Journal of Sports Physiology and Performance*, 13(9), 1130-1135.

Collet, C. (2013) The possession game? A comparative analysis of ball retention and team success in European and international football, 2007-2010. *Journal of Sports Sciences*, 31(2), 123-136.

Cooper, S., Hughes, M., O'Donoghue, P. & Nevill, A. (2007) A simple statistical method for assessing the reliability of data entered into sports performance analysis systems. *International Journal of Performance Analysis in Sport*, 7(1), 87-109.

Coutts, A. (2014a) In the age of technology, Occam's razor still applies. *International Journal of Sports Physiology and Performance*, 9(5), 741. Coutts, A. (2014b) Evolution of football match analysis research. *Journal of Sports Sciences*, 32(30), 1829-1830.

Coutts, A. (2016) Working fast and working slow: the benefit of embedding research in high performance sport. *International Journal of Sports Physiology and Performance*, 11(1), 1-2.

Coutts, A. (2017) Challenges in developing evidence-based practice in high-performance sport. International Journal of Sports Physiology and Performance, 12(6), 717-718.

Crolley, L., Hand, D. & Jeutter, R. (2000) Playing the identity card: stereotypes in European football. *Soccer and Society*, 1(2), 107-128.

Cross, R., Siegler, J., Marshall, P. & Lovell, R. (2019) Scheduling of training and recovery during the in-season weekly microcycle: insights from team sport practitioners. *European Journal of Sport Science*, 19(10), 1287-1296.

Cummins, C., Orr, R., O'Connor, H. & West, C. (2013) Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Medicine*, 43(10), 1025-1042.

Cushion, C. & Jones, R. (2001) A systematic observation of professional top-level youth soccer coaches. *Journal of Sport Behaviour*, 24(4), 354-376.

Cushion, C., Ford, P. & Williams, A. (2012) Coach behaviours and practice structures in youth soccer: implications for talent development. *Journal of Sports Sciences*, 30(15), 1631-1641.

Cust, E., Sweeting, A., Ball, K. & Robertson, S. (2019) Machine and deep learning for sport-specific movement recognition: a systematic review of model development and performance. *Journal of Sports Sciences*, 37(5), 568-600.

Cust, E., Sweeting, A., Ball, K. & Robertson, S. (2021) Classification of Australian football kick types in-situation via ankle-mounted inertial measurement units. *Journal of Sports Sciences,* online ahead of print.

Dadashi, F., Crettenand, F., Millet, G. & Aminian, K. (2012) Front-crawl instantaneous velocity estimation using a wearable inertial measurement unit. *Sensors*, 12(10), 927-939.

Dadashi, F., Crettenand, F., Millet, G., Seifert, L., Komar, J. & Aminian, K. (2013) Automatic frontcrawl temporal phase detection using adaptive filtering of inertial signals. *Journal of Sports Sciences*, 31(11), 1251-1260. Dalen, T., Jørgen, I., Gertjan, E., Havard, H. & Ulrik, W. (2016) Player load, acceleration, and deceleration during forty-five competitive matches of elite soccer. *The Journal of Strength and Conditioning Research*, 30(2), 351-359.

Dalton-Barron, N., Whitehead, S., Roe, G., Cummins, C., Beggs, C. & Jones, B. (2020) Time to embrace the complexity when analysing GPS data? A systematic review of contextual factors on match running in rugby league. *Journal of Sports Sciences*, 38(10), 1161-1180.

David, G. (2005) Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. *Occupational Medicine*, 55(3), 190-199.

Davids, K. (2008) Designing representative task constraints for studying visual anticipation in fast ball sports: what we can learn from past and contemporary insights in neurobiology and psychology. *International Journal of Sport Psychology*, 39(2), 166-177.

Delaney, J., Scott, T., Thornton, H., Bennett, K., Gay, D., Duthie, G. & Dascombe, B. (2015) Establishing duration-specific running intensities from match-play analysis in rugby league. *International Journal of Sports Physiology and Performance*, 10(6), 725-731.

Dellal, A., Chamari, K., Wong, D., Ahmaidi, S., Keller, D., Barros, R., Bisciotti, G. & Carling, C. (2011a) Comparison of physical and technical performance in European soccer match-play: FA Premier League and La Liga. *European Journal of Sport Science*, 11(1), 51-59.

Dellal, A., Lago-Peñas, C., Wong, D. & Chamari, K. (2011b) Effect of the number of ball contacts within bouts of 4 vs. 4 small-sided games soccer games. *International Journal of Sports Physiology and Performance*, 6(3), 322-333.

Dellal, A., Owen, A., Wong, D., Krustrup, P., Van Exsel, M. & Mallo, J. (2012) Technical and physical demands of small vs. large sided games in relation to playing position in elite soccer. *Human Movement Science*, 31(4), 957-969.

Dellal, A., Wong, D., Moalla, W. & Chamari, K. (2010) Physical and technical activity of soccer players in the French first league - with special reference to their playing position. *International SportMed Journal*, 11(2), 278-290.

Deloitte (2020) Home truths: annual review of football finance. London: Deolitte.

Di Mascio, M. & Bradley, P. (2013) Evaluation of the most intense high-intensity running period in English FA Premier League soccer matches. *The Journal of Strength and Conditioning Research*, 27(4), 909-915.

Di Salvo, V., Baron, R., González-Haro, C., Gormasz, C., Pigozzi, F. & Bachl, N. (2010) Sprinting analysis of elite soccer players during European Champions League and UEFA Cup matches. *Journal of Sports Sciences*, 28(14), 1489-1494.

Di Salvo, V., Collins, A., McNeill, B. & Cardinale, M. (2006) Validation of ProZone<sup>®</sup>: a new videobased performance analysis system. *International Journal of Performance Analysis in Sport*, 6(1), 108-119.

Di Salvo, V., Gregson, W., Atkinson, G., Tordoff, P. & Drust, B. (2009) Analysis of high intensity activity in Premier League soccer. *International Journal of Sports Medicine*, 30(3), 205-212.

Dixon, P., Saint-Maurice, P., Kim, Y., Hibbing, P., Bai, Y. & Welk, G. (2018) A primer on the use of equivalence testing for evaluating measurement agreement. *Medicine and Science in Sport and Exercise*, 50(4), 837-845.

Dörge, H., Andersen, T., Sørensen, H. & Simonsen, E. (2002) Biomechanical differences in soccer kicking with the preferred and the non-preferred leg. *Journal of Sports Sciences*, 20(4), 293-299.

Doshi-Velez, F. & Kim, B. (2017) Towards a rigorous science of interpretable machine learning. ArXiv, 17(2), 1-13.

Drust, B. (2019) Applied science and soccer: a personal perspective on the past, present and future of a discipline. *Sports Performance and Science Reports*, 56(1), 1-7.

Edgecomb, S. & Norton, K. (2006) Comparison of global positioning and computer-based tracking systems for measuring player movement distance during Australian football. *Journal of Science and Medicine in Sport*, 9(1), 25-32.

Edwards, S., White, S., Humphreys, S., Robergs, R. & O'Dwyer, N. (2019) Caution using data from triaxial accelerometers housed in player tracking units during running. *Journal of Sports Sciences*, 37(7), 810-818.

Ehrmann, F. Duncan, C., Sindhusake, D., Franzsen, W. & Green, D. (2016) GPS and injury prevention in professional soccer. *The Journal of Strength and Conditioning Research*, 30(2), 360-367.

Eisenmann, J. (2017) Translational gap between laboratory and playing field: new era to solve old problems in sports science. *Translational Journal of the American College of Sports Medicine*, 2(8), 37-43.

Ellens, S., Blair, S., Peacock, J., Barnes, S. & Ball, K. (2017) Use of accelerometers in Australian football to identify a kick. *35<sup>th</sup> Conference of the International Society of Biomechanics in Sports,* Cologne, Germany, 14-18 June 2017, 218-221.

English Premier League (2011) Elite Player Performance Plan. Available at https://www.goalreports.com/EPLPlan.pdf [Accessed 29/03/2021].

EnglishPremierLeague(2021)Managers.Availableonline:https://www.premierleague.com/managers?se=21&cl=-1[Accessed 26/02/2021].

Ericsson, K., Krampe, R., Tesch-Römer, C. (1993) The role of deliberate practice in the acquisition of expert performance. *Psychological Review*, 100(3), 363-406.

Errekagorri, I., Castellano, J., Echeazarra, I. & Lago-Peñas, C. (2020) The effects of the Video Assistant Referee system (VAR) on the playing time, technical-tactical and physical performance in elite soccer. *International Journal of Performance Analysis in Sport*, 20(5), 808-817.

Farrow, D. & Robertson, S. (2017) Development of a skill acquisition periodisation framework for high-performance sport. *Sports Medicine*, 47(6), 1043-1054.

Farrow, D., Baker, J. & MacMahon, C. (2012) Developing sport expertise. London: Routledge.

Fawcett, T. (2006) An introduction to ROC analysis. Pattern Recognition Letters, 27(8), 861-874.

Fédération Internationale de Football Association (2015) *Laws of the Game.* Zurich, Fédération Internationale de Football Association.

Fédération Internationale de Football Association (2019a) *Global Transfer Market Report*. Zurich,Fédération Internationale de Football Association.

Fédération Internationale de Football Association (2019b) *Professional Football Report*. Zurich,Fédération Internationale de Football Association.

Fédération Internationale de Football Association (2020) *FIFA Quality Programme for IMS Wearable EPTS Devices*. Zurich, Fédération Internationale de Football Association. Fédération Internationale de Football Association (2021) Football Technology Resource Hub.Availableonline:https://football-technology.fifa.com/en/resource-hub/certified-product-database/football-technologies/epts/certified-systems/ [Accessed 04/03/2021].

Ferraz, R., Van Den Tillaar, R. & Marques, M. (2012) The effect of fatigue on kicking velocity in soccer players. *Journal of Human Kinetics*, 35(1), 97-107.

Ferraz, R., Van Den Tillaar, R., Pereira, A. & Marques, M. (2019) The effect of fatigue and duration knowledge of exercise on kicking performance in soccer players. *Journal of Sport and Health Science*, 8(6), 567-573.

Field, A., Harper, L., Chrismas, B., Fowler, P., McCall, A., Paul, D., Chamari, K. & Taylor, L. (2021) The use of recovery strategies in professional soccer: a worldwide survey. *International Journal of Sports Physiology and Performance*, 16(5), 1-12.

Figo, D., Diniz, P., Ferreira, D. & Cardoso, J. (2010) Preprocessing techniques for context recognition from accelerometer data. *Personal and Ubiquitous Computing*, 14(7), 645-662.

Football Association (2020a) *Professional Football Suspended in England until Friday 3<sup>rd</sup> April at the Earliest*. Available online: https://www.thefa.com/news/2020/mar/13/fa-premier-league-efl-statement-football-suspended-130320 [Accessed 22/09/2020].

Football Association (2020b) *Handbook*. Available online: https://www.thefa.com/football-rules-governance/lawsandrules/fa-handbook [Accessed 01/09/2020].

Ford, P., De Ste Croix, M., Lloyd, R., Meyers, R., Moosavi, M., Oliver, J., Till, K. & Williams, C. (2011) The long-term athlete development model: physiological evidence and application. *Journal of Sports Sciences*, 29(4), 389-402.

Ford, P., Yates, I. & Williams, A. (2010) An analysis of practice activities and instructional behaviours used by youth soccer coaches during practice: exploring the link between science and application. *Journal of Sports Sciences*, 28(5), 483-495.

Forman, G. & Scholz, M. (2010) Apples-to-apples in cross-validation studies: pitfalls in classifier performance measurement. *Association for Computing Machinery: Special Interest Group on Knowledge Discovery and Data Mining Explorations Newsletter*, 12(1), 49-57.

Fradua, L., Zubillaga, A., Caro, Ó., Fernández-García, Á., Ruiz-Ruiz, C. & Tenga, A. (2013) Designing small-sided games for training tactical aspects in soccer: extrapolating pitch sizes from full-size professional matches. *Journal of Sports Sciences*, 31(6), 573-581.

Francis, J. & Jones, G. (2014) Elite rugby union players perceptions of performance analysis. International Journal of Performance Analysis in Sport, 14(1), 188-207.

Francis, J., Owen, A. & Peters, D. (2019) A new reliable performance analysis template for quantifying action variables in elite men's wheelchair basketball. *Frontiers in Psychology*, 10(16), 1-12.

Frencken, W., Lemmink, K. & Delleman, N. (2010) Soccer specific accuracy and validity of the local position measurement (LPM) system. *Journal of Science and Medicine in Sport*, 13(6), 641-645.

Frencken, W., Lemmink, K., Delleman, N. & Visscher, C. (2011) Oscillations of centroid position and surface area of soccer teams in small-sided games. *European Journal of Sports Science*, 11(4), 215-223.

Frick, B. (2007) The football players' labour market: empirical evidence from the major European leagues. *Scottish Journal of Political Economy*, 54(3), 422-446.

Frodl, C. (2015) Commercialisation of sports data: rights of event owners over information and statistics generated about their sports events. *Marquette Sports Law Review*, 26(1), 55-90.

Fry, R., Morton, A. & Keast, D. (1992) Periodisation of training stress - a review. *Canadian Journal of Sport Sciences*, 17(3), 234-240.

Fullagar, H., Harper, L., Govus, A., McCunn, R., Eisenmann, J. & McCall, A. (2019b) Practitioner perceptions of evidence-based practice in elite sport in the United States of America. *The Journal of Strength and Conditioning Research*, 33(11), 2897-2904.

Fullagar, H., McCall, A., Impellizzeri, F., Favero, T. & Coutts, A. (2019a) The translation of sport science research to the field: a current opinion and overview on the perceptions of practitioners, researchers and coaches. *Sports Medicine*, 49(12), 1817-1824.

Gabbett, T. (2013) Quantifying the physical demands of collision sports: does microsensor technology measure what it claims to measure? *The Journal of Strength and Conditioning Research*, 27(8), 2319-2322.

Gabbett, T., Jenkins, D. & Abernethy, B. (2010) Physical collisions and injury during professional rugby league skills training. *Journal of Science and Medicine in Sport*, 13(6), 578-583.

Gabbett, T., Kearney, S., Bisson, L., Collins, J., Sikka, R., Winder, N., Sedgewick, C., Hollis, E. & Bettle, J. (2018) Seven tips for developing and maintaining a high performance sports medicine team. *British Journal of Sports Medicine*, 52(10), 5-6.

Gambetta, V. (2004) Periodisation and the systematic sport development process. *Olympic Coach*, 16(2), 8-13.

Gastin, P., McLean, O., Breed, R. & Spittle, M. (2014) Tackle and impact detection in elite Australian football using wearable microsensor technology. *Journal of Sports Sciences*, 32(10), 947-953.

Gastin, P., McLean, O., Spittle, M. & Breed, R. (2013) Quantification of tackling demands in professional Australian football using integrated wearable athlete tracking technology. *Journal of Science and Medicine in Sport*, 16(6), 589-593.

Gaudino, P., Alberti, G. & Iaia, F. (2014) Estimated metabolic and mechanical demands during different small-sided games in elite soccer players. *Human Movement Science*, 36(1), 123-133.

Géron, A. (2019) *Hands-on machine learning with Scikit-Learn, Keras and TensorFlow*. Newton: O'Reilly Media Inc.

Glazier, P. (2010) Augmenting golf practice through the manipulation of physical and informational constraints. In Renshaw, I., Davids, K. & Savelsbergh, G. (eds) *Motor learning in practice: a constraints-led approach*. London: Routledge, 187-199.

Gómez-Ruano, M., Lago-Peñas, C. & Pollard, R. (2013) Situational variables. In McGarry, T., O'Donoghue, P. & Sampaio, J. (eds) *Handbook of sports performance analysis*. London: Routledge, 259-269.

Gonçalves, B., Figueira, B., Maçãs, V. & Sampaio, J. (2014) Effect of player position on movement behaviour, physical and physiological performances during an 11-a-side football game. *Journal of Sports Sciences*, 32(2), 191-199.

Gong, B., Cui, Y., Gai, Y., Yi, Q. & Gómez-Ruano, M. (2019) The validity and reliability of live football match statistics from Champdas master match analysis system. *Frontiers in Psychology*, 10(1), 1339-1351.

González-García, I., Martínez, L., Santasmarinas, J. & Gómez-Ruano, M. (2016) Inter-observer reliability of a real-time observation tool in Handball. *International Journal of Kinesiology and Sports Science*, 4(4), 1-9.

Greig, M. & Walker-Johnson, C. (2007) The influence of soccer-specific fatigue on functional stability. *Physical Therapy in Sport*, 8(4), 185-190.

Groom, R., Cushion, C. & Nelson, L. (2011) The delivery of video-based performance analysis by England youth soccer coaches: towards a grounded theory. *Journal of Applied Sport Psychology*, 23(1), 16-32.

Grout, H. & Long, G. (2009) *Improving Teaching and Learning in Physical Education*. Maidenhead, McGraw-Hill Education.

Guadagnoli, M. & Lee, T. (2004) Challenge point: a framework for conceptualising the effects of various practice conditions in motor learning. *Journal of Motor Behaviour*, 36(2), 212-224.

Guex, K. & Millet, G. (2013) Conceptual framework for strengthening exercises to prevent hamstring strains. *Sports Medicine*, 43(12), 1207-1215.

Guilherme, J., Garganta, J., Graça, A. & Seabra, A. (2015) Influence of non-preferred foot technical training in reducing lower limbs functional asymmetry among young football players. *Journal of Sports Sciences*, 33(17), 1790-1798.

Haaland, E. & Hoff, J. (2003) Non-dominant leg training improves the bilateral motor performance of soccer players. *Scandinavian Journal of Medicine and Science in Sports*, 13(3), 179-184.

Halilaj, E., Rajagopal, A., Fiterau, M., Hicks, J., Hastie, T & Delp, S. (2018) Machine learning in human movement biomechanics: best practices, common pitfalls, and new opportunities. *Journal of Biomechanics*, 81(1), 1-11.

Halouani, J., Chtourou, C., Gabbett, T., Chaouachi, A. & Chamri, K. (2014) Small-sided games in team sports training: a brief review. *The Journal of Strength and Conditioning Research*, 28(12), 3594-3618.
Halson, S., Hahn, A. & Coutts, A. (2019) Combining research with "servicing" to enhance sports performance. *International Journal of Sports Physiology and Performance*, 14(5), 549-550.

Harding, J., Mackintosh, C., Hahn, A. & James, D. (2008) Classification of aerial acrobatics in elite half-pipe snowboarding using body mounted inertial sensors. *The Engineering of Sport*, 7(2), 447-456.

Harley, J., Lovell, R., Barnes, C., Portas, M. & Weston, M. (2011) The interchangeability of global positioning system and semiautomated video-based performance data during elite soccer match play. *The Journal of Strength & Conditioning Research*, 25(8), 2334-2336.

Harper, L., West, D., Stevenson, E. & Russell, M. (2014) Technical performance reduces during the extra-time period of professional soccer match-play. *PloS One*, 9(10), 1-6.

Harrop, K. & Nevill, A, (2014) Performance indicators that predict success in an English professional league one soccer team. *International Journal of Performance Analysis in Sport*, 14(3), 907-920.

Hill-Haas, S., Coutts, A., Dawson, B. & Rowsell, G. (2010) Time-motion characteristics and physiological responses of small-sided games in elite youth players: the influence of player number and rule changes. *The Journal of Strength and Conditioning Research*, 24(8), 2149-2156.

Hill-Haas, S., Dawson, B., Impellizzeri, F. & Coutts, A. (2011) Physiology of small-sided games training in football. *Sports Medicine*, 41(3), 199-220.

Hills, S., Barrett, S., Busby, M., Kilduff, L., Barwood, M., Radcliffe, J., Cooke, C. & Russell, M. (2020a) Profiling the post-match top-up conditioning practices of professional soccer substitutes: an analysis of contextual influences. *The Journal of Strength and Conditioning Research*, 34(10), 2805-2814.

Hills, S., Barwood, M., Radcliffe, J., Cooke, C., Kilduff, L., Cook, C. & Russell, M. (2018) Profiling the responses of soccer substitutes: a review of current literature. *Sports Medicine*, 48(10), 2255-2269.
Hills, S., Radcliffe, J., Barwood, M., Arent, S., Cooke, C. & Russell, M. (2020b) Practitioner perceptions regarding the practices of soccer substitutes. *PloS One*, 15(2), 1-24.

Hodges, N. & Williams, A. (2012) Skill acquisition in sport. London: Routledge.

Hodgson, C., Akenhead, R. & Thomas, K. (2014) Time-motion analysis of acceleration demands of 4v4 small-sided soccer games played on different pitch sizes. *Human Movement Science*, 33(1), 25-32. Hölmich, P., Thorborg, K., Dehlendorff, C., Krogsgaard, K. & Gluud, C. (2014) Incidence and clinical presentation of groin injuries in sub-elite male soccer. *British Journal of Sports Medicine*, 48(16), 1425-1250.

Hopkins, W. & Wolfinger, R. (1998) Estimating "individual differences" in the response to an experimental treatment. *Medicine and Science in Sport and Exercise*, 30(5), 125-135.

Hopkins, W., Marshall, S., Batterham, A. & Hanin, J. (2009) Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise*, 41(1), 3-12.

Hoppe, M., Baumgart, C., Polglaze, T. & Freiwald, J. (2018) Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *PloS One*, 13(2), 1-21.

Hopwood, M., MacMahon, C., Farrow, D. & Baker, J. (2015) Is practice the only determinant? Revisiting Starkes (2000). *International Journal of Sports Psychology*, 46(6), 631-651.

Hughes, M. & Bartlett, R. (2002) The use of performance indicators in performance analysis. *Journal* of Sports Sciences, 20(10), 739-754.

Hughes, M. & Franks, I. (2004) Notational analysis - a review of the literature. In Hughes, M. & Franks,I. (eds) *Notational analysis of sports - systems for better coaching and performance in sport*. London:Routledge, 59-106

Hughes, M. & Franks, I. (2015) Essentials of performance analysis in sport. London: Routledge.

Hughes, M., Caudrelier, T., James, N., Redwood-Brown, A., Donnelly, I., Kirkbride, A. & Duschesne,C. (2012) Moneyball and soccer - an analysis of the key performance indicators of elite male soccerplayers by position. *Journal of Human Sport and Exercise*, 7(2), 402-412.

Hughes, M., Evans, S. & Wells, J. (2001) Establishing normative profiles in performance analysis. *International Journal of Performance Analysis in Sport*, 1(1), 1-26.

Hulka, K., Weisser, R. & Belka, J. (2016) Effect of the pitch size and presence of goalkeepers on the work load of players during small-sided soccer games. *Journal of Human Kinetics*, 51(1), 175-181.

Hunter, F., Bray, J., Towlson, C., Smith, M., Barrett, S., Madden, J., Abt, G. & Lovell, R. (2015) Individualisation of time-motion analysis: a method comparison and case report series. *International Journal of Sports Medicine*, 36(1), 41-48.

Impellizzeri, F., Marcora, S. & Coutts, A. (2019) Internal and external training load: 15 years on. International Journal of Sports Science and Performance, 14(2), 270-273.

Impellizzeri, F., Menaspà, P., Coutts, A., Kalkhoven, J. & Menaspà, M. (2020) Training load and its role in injury prevention, part I: back to the future. *Journal of Athletic Training*, 55(9), 885-892.

Impellizzeri, F., Rampinini, E. & Marcora, S. (2005) Physiological assessment of aerobic training in soccer. *Journal of Sports Sciences*, 23(6), 583-592.

Impellizzeri, F., Rampinini, E., Coutts, A., Sassi, A. & Marcora, S. (2004) Use of RPE-based training load in soccer. *Medicine and Science in Sport and Exercise*, 36(6), 1042-1047.

International Football Association Board (2020) *Laws of the Game*. Available online: https://www.theifab.com/log-documents [Accessed 10<sup>th</sup> February 2021].

Issurin, V. (2010) New horizons for the methodology and physiology of training periodisation. *Sports Medicine*, 40(3), 189-206.

Issurin, V. (2016) Benefits and limitations of block periodised training approaches to athletes' preparation: a review. *Sports Medicine*, 46(3), 329-338.

James, N., Mellalieu, S. & Jones, N. (2005) The development of position-specific performance indicators in professional rugby union. *Journal of Sports Sciences*, 23(1), 63-72.

Jaspers, A., Brink, M., Probst, S., Frencken, W. & Helsen, W. (2017) Relationships between training load indicators and training outcomes in professional soccer. *Sports Medicine*, 47(3), 533-544.

Jeong, T., Reilly, T., Morton, J., Bae, S., Drust, B. (2011) Quantification of the physiological loading of one week of "pre-season" and one week of "in-season" training in professional soccer players. *Journal of Sports Sciences*, 29(11), 1161-1166.

Jones, B., Till, K., Emmonds, S., Hendricks, S., Mackreth, P., Darrall-Jones, J., Roe, G., McGeechan, I., Mayhew, R., Hunwicks, R. & Potts, N. (2019) Accessing off-field brains in sport: an applied research model to develop practice. *British Journal of Sports Medicine*, 53(13), 791-793.

Jowitt, H., Durussel, J., Brandon, R. & King, M. (2020) Auto detecting deliveries in elite cricket fast bowlers using microsensors and machine learning. *Journal of Sports Sciences*, 38(7), 767-772.

Katis, A. & Kellis, E. (2009) Effects of small-sided games on physical conditioning and performance in young soccer players. *Journal of Sports Science and Medicine*, 8(3), 374-380.

Kautz, T. (2017) *Acquisition, filtering and analysis of positional and inertial data in sports*. Nuremberg: FAU University Press.

Kellis, E. & Katis, A. (2007) Biomechanical characteristics and determinants of instep soccer kick. *Journal of Sports Science and Medicine*, 6(2), 154-165. Kellis, E., Katis, A. & Vrabas, I. (2006) Effects of an intermittent exercise fatigue protocol on biomechanics of soccer kick performance. *Scandinavian Journal of Medicine and Science in Sports*, 16(5), 334-344.

Kelly, D., Coughlan, G., Green, B. & Caulfield, B. (2012) Automatic detection of collisions in elite level rugby union using a wearable sensing device. *Sports Engineering*, 15(2), 81-92.

Kelly, D. & Drust, B. (2009) The effect of pitch dimensions on heart rate responses and technical demands of small-sided soccer games in elite players. *Journal of Science and Medicine in Sport*, 12(4), 475-479.

Kelly, D., Strudwick, A., Atkinson, G., Drust, B. & Gregson, W. (2020) Quantification of training and match-load distribution across a season in elite English Premier League soccer players. *Science and Medicine in Football*, 4(1), 59-67.

Kipling, R. (1902) The just so stories: the elephant's child. London: Tauchintz.

Kite, C. & Nevill, A. (2017) The predictors and determinants of inter-seasonal success in a professional soccer team. *Journal of Human Kinetics*, 58(1), 157-167.

Knapp, B. (1977) Skill in sport: the attainment of proficiency. London, Routledge.

Köklü, Y., Alemdaroğlu, U., Cihan, H. & Wong, D. (2017) Effects of bout duration on players' internal and external loads during small-sided games in young soccer players. *International Journal of Sports Physiology and Performance*, 12(10), 1370-1377.

Köklü, Y., Ersöz, G., Alemdaroglu, U., Asç, A. & Özkan, A. (2012) Physiological responses and timemotion characteristics of 4-a-side small-sided game in young soccer players: the influence of different team formation methods. *The Journal of Strength and Conditioning Research*, 26(11), 3118-3123.

Kraemer, W. & Ratamess, N. (2004) Fundamentals of resistance training: progression and exercise prescription. *Medicine and Science in Sport and Exercise*, 36(4), 674-688.

Krane, V. & Williams, J. (2006) Psychological characteristics of peak performance. *Applied Sport Psychology: Personal Growth to Peak Performance*, 5(1), 207-227.

Krasnoff, J., Kohn, M., Choy, F., Doyle, J., Johansen, K. & Painter, P. (2008) Interunit and intraunit reliability of the RT3 triaxial accelerometer. *Journal of Physical Activity and Health*, 5(4), 527-538.

Krouwer, S. (2008) Why Bland-Altman plots should use X, not (Y+X)/2 when X is a reference method. *Statistics in Medicine*, 27(5), 778-780.

Krustrup, P., Zebis, M., Jensen, J. & Mohr, M. (2010) Game-induced fatigue patterns in elite female soccer. *The Journal of Strength and Conditioning Research*, 24(2), 437-441.

Kyprianou, E., Lolli, L., Al Haddad, H., Di Salvo, V., Varley, M., Villanueva, A., Gregson, W. & Weston, M. (2019) A novel approach to assessing validity in sports performance research: integrating expert practitioner opinion into the statistical analysis. *Science and Medicine in Football*, 3(4), 333-338.

Lacome, M., Piscione, J., Hager, J. & Carling, C. (2016) Analysis of running and technical performance in substitute players in international male rugby union competition. *International Journal of Sports Physiology and Performance*, 11(6), 783-792.

Lago-Peñas, C. & Sampaio, J. (2015) Just how importance is a good season start? Overall team performance and financial budget of elite soccer clubs. *Journal of Sports Sciences*, 33(12), 1214-1218. Lago-Peñas, C., Gómez-Ruano, M., Megías-Navarro, D. & Pollard, R. (2016) Home advantage in football: examining the effect of scoring first on match outcome in the five major European leagues. *International Journal of Performance Analysis in Sport*, 16(2), 411-421.

Lago, C. (2009) The influence of match location, quality of opposition and match status on possession strategies in professional association football. *Journal of Sports Sciences*, 27(13), 1463-1469.

Lambert, M., Viljoen, W., Bosch, A., Pearce, A. & Sayers, M. (2008) General principles of training. In Schwellnus, M. (ed) *Olympic textbook of medicine in sport*. Chichester: Blackwell Publishing, 1-48. Langsdon, R. (2015) *Strange technology allows us all to train like champions*. Available online: https://planetinnovation.com/perspectives/strange-technology-allows-us-train-like-champions/ [Accessed 20/08/2021].

Lapham, A. & Bartlett, R. (1995) The use of artificial intelligence in the analysis of sports performance: a review of applications in human gait analysis and future directions for sports biomechanics. *Journal of Sports Sciences*, 13(3), 229-237.

LeCun, Y., Bengio, Y. & Hinton, G. (2015) Deep learning. Nature, 521(1), 436-444.

Lees, A., Asai, T., Andersen, T., Nunome, H. & Sterzing, T. (2010) The biomechanics of kicking in soccer: a review. *Journal of Sports Sciences*, 28(8), 805-817.

Lewis, T. (2014) How computer analysts took over at Britain's top football clubs. *The Guardian*, 9 March [Online]. Available at: https://www.theguardian.com/football/2014/mar/09/premier-league-football-clubs-computer-analysts-managers-data-winning [Accessed 15/12/2020].

Littlewood, M., Mullen, C. & Richardson, D. (2011) Football labour migration: an examination of the player recruitment strategies of the 'big five' European football leagues 2004-5 to 2008-9. *Soccer and Society*, 12(6), 788-805.

Liu, H., Gómez-Ruano, M. Gonçalves, B. & Sampaio, J. (2016) Technical performance and match-tomatch variation in elite football teams. *Journal of Sports Sciences*, 34(6), 509-518.

Liu, H., Hopkins, W., Gómez-Ruano, M & Molinuevo, S. (2013) Inter-operator reliability of live football match statistics from OPTA Sportsdata. *International Journal of Performance Analysis in Sport*, 13(3), 803-821.

Liu, H., Yi, Q., Giménez, J., Gómez-Ruano, M. & Lago-Peñas, C. (2015) Performance profiles of football teams in the UEFA Champions League considering situational efficiency. *International Journal of Performance Analysis in Sport*, 15(1), 371-390.

Los Arcos, A., Mendez-Villanueva, A. & Martínez-Santos, R. (2017) In-season training periodisation of professional soccer players. *Biology of Sport*, 34(2), 149-155.

Lovell, R., Towlson, C., Parkin, G., Portas, M., Vaeyens, R. & Cobley, S. (2015) Soccer player characteristics in English lower league development programmes: the relationships between relative age, maturation, anthropometry and physical fitness. *PloS One*, 10(9), 1-14.

Luinge, H. & Vetlink, P. (2005) Measuring orientation of human body segments using miniature gyroscopes and accelerometers. *Medical and Biological Engineering and Computing*, 42(2), 273-282.

Lutz, J., Memmert, D., Raabe, D., Dornberger, R. & Donath, L. (2020) Wearables for integrative performance and tactic analyses: opportunities, challenges and future directions. *International Journal of Environmental Research and Public Health*, 17(1), 59-85.

Ma, J., Ding, Y., Cheng, J., Tan, Y., Gan, V. & Zhang, J. (2019) Analysing the leading causes of traffic fatalities using XGBoost and grid-based analysis: a city management perspective. *Institute of Electrical and Electronics Engineers Access*, 7(1), 148059-148072.

Mackenzie, R. & Cushion, C. (2013) Performance analysis in football: a critical review and implications for future research. *Journal of Sports Sciences*, 31(6), 639-676.

Magill, R. & Anderson, D. (2017) *Motor learning: concepts and applications*. Maidenhead: McGraw-Hill Education.

Malone, J., Barrett, S., Barnes, C., Twist, C. & Drust, B. (2020) To infinity and beyond: the use of GPS devices within the football codes. *Science and Medicine in Football*, 4(1), 82-84.

Malone, J., Di Michele, R., Morgans, R., Burgess, D., Morton, J. & Drust, B. (2015) Seasonal training load quantification in elite English Premier League soccer players. *International Journal of Sports Physiology and Performance*, 10(4), 489-497.

Malone, J., Harper, L., Jones, B., Perry, J., Barnes, C. & Towlson, C. (2019) Perspectives of applied collaborative sport science research within professional team sports. *European Journal of Sport Science*, 19(2), 147-155.

Malone, J., Lovell, R., Varley, M. & Coutts, A. (2017) Unpacking the black box: applications and considerations for using GPS devices in sport. *International Journal of Sports Physiology and Performance*, 12(2), 18-26.

Mannini, A. & Sabatini, A. (2010) Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors*, 10(2), 1154-1175.

Manzi, V., Bovenzi, A., Impellizzeri, M., Carminati, I. & Castagna, C. (2013) Individual training-load and aerobic-fitness variables in premiership soccer players during the precompetitive season. *The Journal of Strength and Conditioning Research*, 27(3), 631-636.

Manzi, V., D'Ottavio, S., Impellizzeri, F., Chaouachi, A., Chamari, K. & Castagna, C. (2010) Profile of weekly training load in elite male professional basketball players. *The Journal of Strength and Conditioning Research*, 24(5), 1399-1406.

Marcora, S., Staiano, W. & Manning, V. (2009) Mental fatigue impairs physical performance in humans. *Journal of Applied Physiology*, 106(3), 857-864.

Martín-García, A., Díaz, A., Bradley, P., Morera, F. & Casamichana, D. (2018) Quantification of a professional football team's external load using a microcycle structure. *The Journal of Strength and Conditioning Research*, 32(12), 3511-3518.

Martindale, R. & Nash, C. (2013) Sports science relevance and application: perceptions of UK coaches. *Journal of Sports Sciences*, 31(8), 807-819.

Martinez-Lagunas, V., Niessen, M. & Hartmann, U. (2014) Women's football: player characteristics and demands of the game. *Journal of Sport and Health Science*, 3(4), 258-272.

Matveyev, L. (1981) Fundamentals of sport training. Moscow: Progress Publishers.

McArdle. S., Martin, D., Lennon, A. & Moore, P. (2010) Exploring debriefing in sports: a qualitative perspective. *Journal of Applied Sport Psychology*, 22(3), 320-332.

McCall, A., Davison, M., Carling, C., Buckthorpe, M., Coutts, A. & Dupont, G. (2016a) Can off-field 'brains' provide a competitive advantage in professional football? *British Journal of Sports Medicine*, 50(12), 710-712.

McCall, A., Dupont, G. & Ekstrand, J. (2016b) Injury prevention strategies, coach compliance and player adherence of 33 of the UEFA Elite Club Injury Study teams: a survey of teams' head medical officers. *British Journal of Sports Medicine*, 50(12), 725-730.

McGarry, T. (2009) Applied and theoretical perspectives of performance analysis in sport: scientific issues and challenges. *International Journal of Performance Analysis in Sport*, 9(1), 128-140.

McGrath, J., Neville, J., Stewart, T. & Cronin, J. (2019) Cricket fast bowling detection in a training setting using an inertial measurement unit and machine learning. *Journal of Sports Sciences*, 37(11), 1220-1226.

McGuigan, M., Cormack, S. & Rowell, A. (2018) Industry based postgraduate scholarships in highperformance sport. *Sports Performance and Science Reports*, 20(1), 1-2.

McLaren, S., Macpherson, T., Coutts, A., Hurst, C., Spears, I. & Weston, M. (2018) The relationships between internal and external measures of training load and intensity in team sports: a meta-analysis. *Sports Medicine*, 48(3), 641-658.

McLaren, S., Smith, A., Spears, I. & Weston, M. (2017) A detailed quantification of differential ratings of perceived exertion during team sport training. *Journal of Science and Medicine in Sport*, 20(3), 290-295.

McMorris, T. (2004) Acquisition and performance of sports skills. Hoboken: Wiley.

McNamara, D., Gabbett, T., Chapman, P., Naughton, G. & Farhart, P. (2015) The validity of microsensors to automatically detect bowling events and counts in cricket fast bowlers. *International Journal of Sports Physiology and Performance*, 10(1), 71-75.

McParland, A., Ackery, A. & Detsky, A. (2020) Advanced analytics to improve performance: can healthcare replicate the success of professional sports? *British Medical Journal - Quality and Safety*, 29(5), 405-408.

Messersmith, L. & Corey, S. (1931) The distance traversed by a basketball player. *Research Quarterly: American Physical Education Association*, 2(2), 57-60.

Morgans, R., Adams, D., Mullen, R., McLellan, C. & Williams, M. (2014b) Technical and physical performance over an English championship league season. *International Journal of Sports Science and Coaching*, 9(5), 1033-1042.

Morgans, R., Di Michele, R. & Drust, B. (2018) Soccer match play as an important component of the power-training stimulus in Premier League players. *International Journal of Sports Physiology and Performance*, 13(5), 665-667.

Morgans, R., Orme, P., Anderson, L. & Drust, B. (2014a) Principles and practices of training for soccer. *Journal of Sport and Health Science*, 3(4), 251-257.

Mujika, I., Halosn, S., Burke, L., Balagué, G. & Farrow, D. (2018) An integrated, multifactorial approach to periodisation for optimal performance in individual and team sports. *International Journal of Sports Physiology and Performance*, 13(5), 538-561.

Mujika, I., Padilla, S., Pyne, D. & Busso, T. (2004) Physiological changes associated with the pre-event taper in athletes. *Sports Medicine*, 34(13), 891-927.

Nagasawa, Y., Demura, S., Matsuda, s., Uchida, Y. & Demura, T. (2011) Effect of differences in kicking legs, kick directions and kick skill on kicking accuracy in soccer players. *Journal of Quantitative Analysis in Sports*, 7(4), 1-11.

Nassis, G. (2017) Leadership in science and medicine: can you see the gap? *Science and Medicine in Football*, 1(3), 195-196.

Nédélec, M., Halson, S., Abaidia, A., Ahmaidi, S. & Dupont, G. (2015a) Stress, sleep and recovery in elite soccer: a critical review of the literature. *Sports Medicine*, 45(10), 1387-1400.

Nédélec, M., Halson, S., Delecroix, B., Abaidia, A., Ahmaidi, S. & Dupont, G. (2015b) Sleep hygiene and recovery strategies in elite soccer players. *Sports Medicine*, 45(11), 1547-1559.

Nedergaard, N., Robinson, M., Eusterweimann, E., Drust, B., Lisboa, P. & Vanrenterghem, J. (2017) The relationship between whole-body external loading and body-worn accelerometery during teamsport movements. *International Journal of Sports Physiology and Performance*, 12(1), 18-26.

Nelson, L. & Groom, R. (2012) The analysis of athletic performance: some practical and philosophical considerations. *Sport, Education and Society*, 17(5), 687-701.

Nelson, L., Potrac, P. & Groom, R. (2014) Receiving video-based feedback in elite ice-hockey: a player's perspective. *Sport, Education and Society*, 19(1), 19-40.

Nevill, A., Atkinson, G. & Hughes, M. (2008) Twenty-five years of sport performance research in the Journal of Sports Sciences. *Journal of Sports Sciences*, 26(4), 413-426.

Nevill, A., Lane, A., Kilgour, L., Bowes, N. & Whyte, G. (2001) Stability of psychometric questionnaires. *Journal of Sports Sciences*, 19(4), 273-278.

Ngo, J., Tsui, M., Smith, A., Carling, C., Chan, G. & Wong, D. (2012) The effects of man-marking on work intensity in small-sided soccer games. *Journal of Sports Science and Medicine*, 11(1), 109-114.

Nicholas, C., Nuttall, F. & Williams, C. (2000) The Loughborough Intermittent Shuttle Test: a field test that simulates the activity pattern of soccer. *Journal of Sports Sciences*, 18(2), 97-104.

Norris, S. & Smith, D. (2002) Planning, periodisation, and sequencing of training and competition: the rationale for a competently planned, optimally executed training and competition program, supported by a multidisciplinary team. In Kellmann, M. (ed) *Enhancing recovery: preventing underperformance in athletes*. Champaign: Human Kinetics, 121-141.

Norton, K. & Olds, T. (2001) Morphological evolution of athletes over the 20<sup>th</sup> century. *Sports Medicine*, 31(11), 763-783.

Nosek, P., Brownlee, T., Drust, B. & Andrew, M. (2021) Feedback of GPS training data within professional English soccer: a comparison of decision making and perceptions between coaches, players and performance staff. *Science and Medicine in Football*, 5(1), 35-47.

Nunome, H., Ikegami, Y., Kozakai, R., Apriantono, T. & Sano, S. (2006) Segmental dynamics of soccer instep kicking with the preferred and non-preferred leg. *Journal of Sports Sciences*, 24(5), 529-541.

O'Connor, D., Larkin, P. & Williams, A. (2017) What learning environment help improve decisionmaking? *Physical Education and Sport Pedagogy*, 22(6), 647-660.

O'Donoghue, P. (2005) Normative profiles of sports performance. *International Journal of Performance Analysis in Sport*, 5(1), 104-119.

O'Donoghue, P. (2007) Reliability issues in performance analysis. *International Journal of Performance Analysis in Sport*, 7(1), 35-48.

O'Donoghue, P. (2010) Research methods for sports performance analysis. London: Routledge.

O'Donoghue, P. (2013) Match analysis for coaches. In Jones, R. & Kingston, K. (eds) *An introduction to sports coaching: connecting theory to practice*. London: Routledge, 161-176.

O'Donoghue, P. & Holmes, L. (2015) Data analysis in sport. London: Routledge.

O'Donoghue, P. & Mayes, A. (2013) Performance analysis, feedback and communication in coaching. In McGarry, T., O'Donoghue, P. & Sampaio, J. (eds) *Handbook of sports performance analysis*. London: Routledge, 155-164.

O'Reilly, M., Caulfield, B., Ward, T., Johnston, W. & Doherty, C. (2018) Wearable inertial sensor systems for lower limb exercise detection and evaluation: a systematic review. *Sports Medicine*, 48(5), 1221-1246.

Oberstone, J. (2009) Differentiating the top English premier league football clubs from the rest of the pack: identifying the keys to success. *Journal of Quantitative Analysis in Sports*, 5(3), 1-27.

Oberstone, J. (2010) Comparing English premier league goalkeepers: identifying the pitch actions that differentiate the best from the rest. *Journal of Quantitative Analysis in Sport*, 6(1), 1-17.

Oberstone, J. (2011) Comparing team performance of the English Premier League, Serie A and La Liga for the 2008-2009 season. *Journal of Quantitative Analysis in Sport*, 7(1), 1-16.

Ofoghi, B., Zeleznikow, J., MacMahon, C. & Dwyer, D. (2013) Supporting athlete selection and strategic planning in track cycling omnium: a statistical and machine learning approach. *Information Sciences*, 233(1), 200-213.

OPTA Sports (2017) Data and Software Services Proposal. London: OPTA.

OPTASports(2018)OPTAEventDefinitions.Availableonline:https://www.optasports.com/news/opta-s-event-definitions/[Accessed 29/04/2020].

OPTA Sports (2020) OPTA ProVision Custom Report. London: OPTA.

OPTA Sports (2021) *The OPTA Difference*. Available online: https://www.optasports.com/about/theopta-difference/ [Accessed 03/03/2021].

Orchard, J., Walt, S., McIntosh, A. & Garlick, D. (1999) Muscle activity during the drop punt kick. *Journal of Sports Sciences*, 17(10), 837-846.

Osgnach, C., Poser, S., Bernardini, R., Rinaldo, R. & Di Prampero, P. (2010) Energy cost and metabolic power in elite soccer: a new match analysis approach. *Medicine and Science in Sports and Exercise*, 42(1), 170-178.

Owen, A., Djaoui, L., Newton, M., Malone, S. & Mendes, B. (2017) A contemporary multi-model mechanical approach to training monitoring in elite professional soccer. *Science and Medicine in Football*, 1(3), 216-221.

Owen, A., Wong, D., McKenna, M. & Dellal, A. (2011) Heart rate responses and technical comparison between small- vs. large-sided games in elite professional soccer. *The Journal of Strength and Conditioning Research*, 25(8), 2104-2110.

Page, R., Marrin, K., Brogden, C. & Greig, M. (2015) Biomechanical and physiological responses to a contemporary soccer match-play simulation. *The Journal of Strength and Conditioning Research*, 29(10), 2860-2866.

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

Parrington, L., Phillips, E., Wong, A., Finch, M., Wain, E. & MacMahon, C. (2016) Validation of inertial measurement units for tracking 100m sprint data. *34<sup>th</sup> International Conference on Biomechanics in Sport*, Tsukuba, Japan, 18-22 July 2016, 442-445.

Partington, M. & Cushion, C. (2013) An investigation of the practice activities and coaching behaviours of professional top-level youth soccer coaches. *Scandinavian Journal of Medicine and Science in Sports*, 23(3), 374-382.

Paul, D., Bradley, P. & Nassis, G. (2015) Factors affecting match running performance of elite soccer players: shedding some light on the complexity. *International Journal of Sports Physiology and Performance*, 10(4), 516-519.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011) Scikit-Learn: machine learning in python. *Journal of Machine Learning Research*, 12(1), 2825-2830.

Pinder, R., Davids, K., Renshaw, I. & Araújo, D. (2011) Representative learning design and functionality of research and practice in sport. *Journal of Sport and Exercise Psychology*, 33(1), 146-155.

PlayerMaker<sup>™</sup> (2017) KPI Definitions. Tel Aviv, PlayerMaker<sup>™</sup>.

PlayerMaker<sup>™</sup> (2021) *Play Smart. Connect Your Game* [Online]. Available from https://playermaker.com [Accessed 26/04/2021].

Plews, D., Laursen, P., Le Meur, Y., Hausswirth, C., Kilding, A. & Buchheit, M. (2014) Monitoring training with heart-rate variability: how much compliance is needed for valid assessment? *International Journal of Sports Physiology and Performance*, 9(5), 783-790.

Pollard, B., Turner, A., Eager, R., Cunningham, D., Cook, C., Hogben, P. & Kilduff, L. (2018) The ball in play demands of international rugby union. *Journal of Science and Medicine in Sport*, 21(10), 1090-1094.

Potrac, P., Jones, R. & Nelson, L. (2014) Interpretivism. In Nelson, L., Groom, R. & Potrac, P. (eds) *Research methods in sports coaching*. London: Routledge, 31-41.

Proske, U. & Morgan, D. (2001) Muscle damage from eccentric exercise: mechanism, mechanical signs, adaptation and clinical applications. *The Journal of Physiology*, 537(2), 333-345.

Rago, V., Brito, J., Figueiredo, P., Costa, J., Barreira, D., Krustrup, P. & Rebelo, A. (2019) Methods to collect and interpret external training load using microtechnology incorporating GPS in professional football: a systematic review. *Research in Sports Medicine*, 28(3), 437-458.

Rahnama, N., Lees, A. & Bambaecichi, E. (2005) A comparison of muscle strength and flexibility between the preferred and non-preferred leg in English soccer players. *Ergonomics*, 48(11-14), 1568-1575.

Rampinini, E., Impellizzeri, F., Castagna, C., Coutts, A. & Wisløff, U. (2009) Technical performance during soccer matches of the Italian Serie A league: effect of fatigue and competitive level. *Journal of Science and Medicine in Sport*, 12(1), 227-233.

Randers, M., Mujika, I., Hewitt, A., Santisteban, J., Bischoff, R., Solano, R., Zubillaga, A., Peltola, E., Krustrup, P. & Mohr, M. (2010) Application of four different football match analysis systems: a comparative study. *Journal of Sports Sciences*, 28(2), 171-182.

Reade, I., Rodgers, W. & Hall, N. (2009) Knowledge transfer: how do high performance coaches access the knowledge of sport scientist? *International Journal of Sports Science and Coaching*, 3(3), 319-334. Redwood-Brown, A., Bussell, C. & Bharaj, H. (2012) The impact of different standards of opponents on observed player performance in the English Premier League. *Journal of Human Sport and Exercise*, 7(2), 341-355.

Reed, D. & Hughes, M. (2006) An exploration of team sport as a dynamical system. *International Journal of Performance Analysis in Sport*, 6(2), 114-125.

Reep, C. & Benjamin, B. (1968) Skill and chance in association football. *Journal of the Royal Statistical Society*, 131(4), 581-585.

Reeves, M. & Roberts, S. (2013) Perceptions of performance analysis in elite youth football. International Journal of Performance Analysis in Sport, 13(1), 200-211.

Reilly, T. (1976) A motion analysis of work-rate in different positional roles in professional football match-play. *Journal of Human Movement Studies*, 2(1), 87-97.

Reilly, T. (2007) *The science of training - soccer: a scientific approach to developing strength, speed and endurance.* London, Routledge.

Reilly, T., Williams, A., Nevill, A. & Franks, A. (2000) A multidisciplinary approach to talent identification in soccer. *Journal of Sports Sciences*, 18(9), 695-702.

Rein, R. & Memmert, D. (2016) Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *SpringerPlus*, 5(1), 1-13.

Rey, E., Lago-Peñas, C., Lago-Ballesteros, J. (2012a) Tensiomyography of selected lower-limb muscles in professional soccer players. *Journal of Electromyography and Kinesiology*, 22(6), 866-872.

Rey, E., Lago-Peñas, C., Lago-Ballesteros, J. & Casáis, L. (2012b) The effect of recovery strategies on contractile properties using tensiomyography and perceived muscle soreness in professional soccer players. *The Journal of Strength and Conditioning Research*, 26(11), 3081-3088.

Ritchie, D., Hopkins, W., Buchheit, M., Cordy, J. & Bartlett, J. (2016) Quantification of training and competition load across a season in an elite Australian football club. *International Journal of Sports Physiology and Performance*, 11(4), 474-479.

Robertson, S. (2020) Man and machine: adaptive tools for the contemporary performance analyst. *Journal of Sports Sciences*, 38(18), 2118-2126.

Robertson, S., Bartlett, J. & Gastin, P. (2017) Red, amber, or green? Athlete monitoring in team sport: the need for decision support systems. *International Journal of Sports Physiology and Performance*, 12(2), 73-79.

Robineau, J., Jouaux, T., Lacroix, M. & Babault, N. (2012) Neuromuscular fatigue induced by a 90minute soccer game modelling. *The Journal of Strength and Conditioning Research*, 26(2), 555-562.

Rösch, D., Hodgson, R., Peterson, L., Graf-Baumann, T., Junge, A., Chomiak, J. & Dvoorak, J. (2000)
Assessment and evaluation of football performance. *The American Journal of Sports Medicine*, 28(5), 29-39.

Rossi, A., Pappalardo, L., Cintia, P., Iaia, F., Fernàndez, J. & Medina, D. (2018) Effective injury forecasting in soccer with GPS training data and machine learning. *PloS One*, 13(7), 1-15.

Rostgaard, T., Iaia, F., Simonsen, D. & Bangsbo, J. (2008) A test to evaluate the physical impact on technical performance in soccer. *The Journal of Strength and Conditioning Research*, 22(1), 283-292.

Rothwell, M., Davids, K., Stone, J., O'Sullivan, M., Vaughan, J., Newcombe, D. & Shuttleworth, R. (2020) A department of methodology can coordinate transdisciplinary sport science support. *Journal of Expertise*, 3(1), 55-65.

Ruiz-Ruiz, C., Fradua, L., Fernández-García, Á. & Zubillaga, A. (2013) Analysis of entries into the penalty area as a performance indicator in soccer. *European Journal of Sport Science*, 13(3), 241-248.

Russell, M., Benton, D. & Kingsley, M. (2010) Reliability and construct validity of soccer skills tests that measure passing, shooting, and dribbling. *Journal of Sports Sciences*, 28(13), 1399-1408.

Russell, M., Benton, D. & Kingsley, M. (2011) The effects of fatigue on soccer skills performed during soccer match simulation. *International Journal of Sports Physiology and Performance*, 6(2), 221-233.

Russell, M., Rees, G. & Kingsley, M. (2013) Technical demands of soccer match play in the English championship. *The Journal of Strength and Conditioning Research*, 27(10), 2869-2873.

Russell, M., Sparkes, W., Northeast, J., Cook, C., Love, T., Bracken, R. & Kilduff, L. (2016) Changes in acceleration and deceleration capacity throughout professional soccer match-play. *Journal of Strength and Conditioning Research*, 30(10), 2839-2844.

Salter, J., De Ste Croix, M., Hughes, J., Weston, M. & Towlson, C. (2021) Monitoring practices of training load and biological maturity in UK soccer academies. *International Journal of Sports Physiology and Performance*, 16(3), 395-406.

Sampaio, J. & Leite, N. (2013) Performance indicators in game sports. In McGarry, T., O'Donoghue, P. & Sampaio, J. (eds) *Handbook of sports performance analysis*. London: Routledge, 115-126.

Sampaio, J. & Maçãs, V. (2012) Measuring tactical behaviour in football. *International Journal of Sports Medicine*, 33(5), 395-401.

Sanderson, F. (1983) A notation system for analysing squash. *Physical Education Review*, 6(1), 19-23. Sanderson, F. & May, K. (1977) The development of objective methods of game analysis in squash rackets. *British Journal of Sports Medicine*, 11(4), 188.

Sapp, R., Spangenburg, E. & Hagberg, J. (2018) Trends in aggressive play and refereeing among the top five European soccer leagues. *Journal of Sports Sciences*, 36(12), 1346-1354.

Sarmento, H., Marcelino, R., Anguera, M., CampaniÇo, J., Matos, N. & Leitão, J. (2014) Match analysis in football: a systematic review. *Journal of Sports Sciences*, 32(20), 1831-1843.

Sarmento, H., Pereira, A., Matos, N., Campaniço, J., Anguera, M. & Leitão, J. (2013) English Premier League, Spain's La Liga and Italy's Serie's A - what's different? *International Journal of Performance Analysis in Sport*, 13(3), 773-789.

Savelsbergh, G., Kamper, W., Rabius, J., De Koning, J. & Schöllhorn, W. (2010) A new method to learn to start in speed skating: a differential learning approach. *International Journal of Sport Psychology*, 41(4), 415-427.

Schielzeth, H., Dingemanse, N., Nakagawa, S., Westneat, D., Allegue, H., Teplitsky, C. Réale, N., Dochtermann, N., Garamszegi, L. & Araya-Ajoy, Y. (2020) Robustness of linear mixed-effects models to violations of distributional assumptions. *Methods in Ecology and Evolution*, 11(9), 1141-1152.

Schmidt, R. & Lee, T. (2005) *Motor learning and control: a behavioural emphasis*. Champaign, Human Kinetics.

Schöllhorn, W., Beckmann, H., Michelbrink, M., Sechelmann, M., Trockel, M. & Davids, K. (2006) Does noise provide a basis for the unification of motor learning theories? *International Journal of Sport Psychology*, 37(2), 186-207.

Schwameder, H. (2008) Biomechanics research in ski jumping, 1991-2006. *Sports Biomechanics*, 7(1), 114-136.

Scott, B., Duthie, G., Thornton, H. & Dascombe, B. (2016a) Training monitoring for resistance exercise: theory and applications. *Sports Medicine*, 46(5), 687-698.

Scott, B., Lockie, R., Knight, T., Clark, A. & De Jonge, X. (2013) A comparison of methods to quantify the in-season training load of professional soccer players. *International Journal of Sports Physiology and Performance*, 8(2), 195-202.

Scott, M., Scott, T. & Kelly, V. (2016b) The validity and reliability of global positioning systems in team sport: a brief review. *The Journal of Strength and Conditioning Research*, 30(5), 1470-1490.

Seyle, H. (1950) Stress and the general adaptation syndrome. *British Medical Journal*, 1(4667), 1383-1392.

Shalev-Shwartz, S. & Ben-David, S. (2014) Understanding machine learning; from theory to algorithm. New York: Cambridge University Press.

Siegle, S. & Lames, M. (2012) Game interruptions in elite soccer. *Journal of Sports Sciences*, 30(7), 619-624.

Silva, J., Rumpf, M., Hertzog, M., Castagna, C., Farooq, A., Girard, O. & Hader, K. (2018) Acute and residual soccer match-related fatigue: a systematic review and meta-analysis. *Sports Medicine*, 48(3), 539-583.

Sinclair, J., Fewtrell, D., Taylor, P., Atkins, S., Bottoms, L. & Hobbs, S. (2014) Three-dimensional kinematic differences between the preferred and non-preferred limbs during maximal instep soccer kicking. *Journal of Sports Sciences*, 32(20), 1914-1923.

Singer, R. (2000) Performance and human factors: considerations about cognition and attention for self-paced and externally paced events. *Ergonomics*, 43(10), 1661-1680.

Smeeton, N., Williams, A., Hodges, N. & Ward, P. (2005) The relative effectiveness of various instructional approaches in developing anticipation skill. *Journal of Experimental Psychology: Applied*, 11(2), 98-110.

Soligard, T., Nilstad, A., Steffen, K., Myklebust, G., Holme, I., Dvorak, J., Bahr, R. & Andersen, T. (2010) Compliance with a comprehensive warm-up programme to prevent injuries in youth football. *British Journal of Sports Medicine*, 44(11), 787-793.

Starkes, J. (2000) The road to expertise: is practice the only determinant? *International Journal of Sports Psychology*, 31(1), 431-451.

Starling, L. & Lambert, M. (2018) Monitoring rugby players for fitness and fatigue: what do coaches want? *International Journal of Sports Physiology and Performance*, 13(6), 777-782.

Steffen, K., Meeuwisse, W., Romiti, M., Kang, J., McKay, C., Bizzini, M., Dvorak, J., Finch, C., Myklebust, G. & Emery, C. (2013) Evaluation of how different implementation strategies of an injury prevention programme (FIFA 11+) impact team adherence and injury risk in Canadian female youth football players: a cluster-randomised trial. *British Journal of Sports Medicine*, 47(8), 480-487.

Stevens, T., De Ruiter, C., Twisk, J., Savelsbergh, G. & Beek, P. (2017) Quantification of in-season training load relative to match load in professional Dutch Eredivisie football players. *Science and Medicine in Football*, 1(2), 117-125.

Stodter, A. & Cushion, C. (2019) Evidencing the impact of coaches' learning: changes in coaching knowledge and practice over time. *Journal of Sports Sciences*, 37(18), 2086-2093.

Stølen, T., Chamari, K., Castagna, C. & Wisløff, U. (2005) Physiology of soccer. Sports Medicine, 35(6), 501-536.

Stone, K. & Oliver, J. (2009) The effect of 45 minutes of soccer-specific exercise on the performance of soccer skills. *International Journal of Sports Physiology and Performance*, 4(2), 163-175.

Stone, K., Oliver, J., Hughes, M., Stembridge, M., Newcombe, D. & Myers, R. (2011) Development of a soccer simulation protocol to include repeated sprints and agility. *International Journal of Sports Physiology and Performance*, 6(3), 427-431.

Svensson, K., Eckerman, M., Alricsson, M., Magounakis, T. & Werner, S. (2018) Muscle injuries of the dominant or non-dominant leg in male football players at elite level. *Knee Surgery, Sports Traumatology, Arthroscopy*, 26(3), 933-937.

Taberner, M., O'Keefe, J., Flower, D., Phillips, J., Close, G., Cohen, D., Richter, C. & Carling, C. (2020) Interchangeability of position tracking technologies: can we merge the data? *Science and Medicine in Football*, 4(1), 76-81.

Taylor, B., Mellalieu, D., James, N. & Barter, P. (2010) Situation variable effects and tactical performance in professional association football. *International Journal of Performance Analysis in Sport*, 10(3), 255-269.

Taylor, J., Mellalieu, S., James, N. & Shearer, D. (2008) The influence of match location, quality of opposition and match status on technical performance in professional association football. *Journal of Sports Sciences*, 26(9), 885-895.

Taylor, J., Wright, A., Dischiavi, S., Townsend, M. & Marmon, A. (2017) Activity demands during multi-directional team sports: a systematic review. *Sports Medicine*, 47(12), 2533-2551.

Tenga, A., Holme, I., Ronglan, L. & Bahr, R. (2010) Effect of playing tactics on achieving score-box possessions in a random series of team possessions from Norwegian professional soccer matches. *Journal of Sports Sciences*, 28(3), 245-255.

Teschke, K., Trask, C., Johnson, P., Chow, Y., Village, J. & Koehoorn, M. (2009) Measuring posture for epidemiology: comparing inclinometry, observations and self-reports. *Ergonomics*, 52(9), 1067-1078.

Thomas, J. & Nelson, J. (1996) Research methods in physical activity. Champaign, Human Kinetics.

Thornton, H., Delaney, J., Duthie, G. & Dascombe, B. (2019) Developing athlete monitoring systems in team sports: data analysis and visualisation. *International Journal of Sports Physiology and Performance*, 14(6), 698-705.

Thorpe, R., Strudwick, A., Buchheit, M., Atkinson, G., Drust, B. & Gregson, W. (2017) The influence of changes in acute training load on daily sensitivity of morning-measured fatigue variables in elite soccer players. *International Journal of Sports Physiology and Performance*, 12(2), 107-113.

Todd, J., Shurley, J. & Todd, T. (2012) Thomas L. DeLorme and the science of progressive resistance exercise. *The Journal of Strength and Conditioning Research*, 26(11), 2913-2923.

Towlson, C., Cobley, S., Parkin, G. & Lovell, R. (2018) When does the influence of maturation on anthropometric and physical fitness characteristics increase and subside? *Scandinavian Journal of Medicine and Science in Sports*, 28(8), 1946-1955.

Towlson, C., MacMaster, C., Gonçalves, B. & Sampaio, J., Toner, J., MacFarlane, N., Barrett, S., Hamilton, A., Jack, R., Hunter, F. and Myers, T. (2021) The effect of bio-banding on physical and psychological indicators of talent identification in academy soccer players. *Science and Medicine in Football*, online ahead of print.

Towlson, C., Salter, J., Ade, J., Enright, K., Harper, L., Page, R. & Malone, J. (2020) Maturityassociated considerations for training load, injury risk, and physical performance within youth soccer: one size does not fit all. *Journal of Sport and Health Science*, online ahead of print.

Trewin, J., Meylan, C., Varley, M. & Cronin, J. (2017) The influence of situational and environmental factors on match-running in soccer: a systematic review. *Science and Medicine in Football*, 1(2), 183-194.

Turner, A & Stewart, P. (2014) Strength and conditioning for soccer players. *Strength and Conditioning Journal*, 36(4), 1-13.

Union of European Football Associations (2020) *Association Club Coefficients*. Available online: https://www.uefa.com/memberassociations/uefarankings/country/ [Accessed 29/04/2020].

Van Der Mars, H. (1989) Observer reliability: issues and procedures. In Darst, P., Zakrajsek, D. & Mancini, V. (eds) *Analysing physical education and sport instruction*. Champaign: Human Kinetics, 53-80.

Van Gool, D., Van Gerven, D. & Boutmans, J. (1988) The Physiological load imposed on soccer players during real match-play. In Reilly, T., Lees, A., Davis, K. & Murphy, W. (eds) *Science and football*. London: E. and F. N. Spon, 51-59.

Van Melick, N., Meddeler, B., Hoogenboom, T., Nijhuis Van Der Sanden, M. & Van Cingel, R. (2017) How to determine leg dominance: the agreement between self-reported and observed performance in healthy adults. *PloS One*, 12(12), 1-9.

Vanrenterghem, J., Nedergaard, N., Robinson, M. & Drust, B. (2017) Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Medicine*, 47(11), 2135-2142.

Varley, M. & Aughey, R. (2013) Acceleration profiles in elite Australian soccer. *International Journal of Sports Medicine*, 34(1), 34-39.

Varley, M., Jaspers, A., Helsen, W. & Malone, J. (2017) Methodological considerations when quantifying high-intensity efforts in team sport using global positioning system technology. *International Journal of Sports Physiology and Performance*, 12(8), 1059-1068.

Verbeek, J., Elferink-Gemser, M., Jonker, L., Huijgen, B. & Visscher, C. (2017) Laterality related to the successive selection of Dutch national youth soccer players. *Journal of Sports Sciences*, 35(22), 2220-2224.

Vergeer, M. & Mulder, L. (2019) Football players' popularity on Twitter explained: performance on the pitch or performance on Twitter? *International Journal of Sport Communication*, 12(3), 376-396. Verheul, J., Nedergaard, N., Vanrenterghem, J. & Robinson, M. (2020) Measuring biomechanical loads in team sports - from lab to field. *Science and Medicine in Football*, 4(3), 246-252.

Vickers, J., Livingston, L., Umeris-Bohnert, S. & Holden, D. (1999) Decision training: the effects of complex instruction, variable practice and reduced delayed feedback on the acquisition and transfer of a motor skill. *Journal of Sports Sciences*, 17(5), 357-367.

Viera, A. & Garrett, J. (2005) Understanding inter-observer agreement: the kappa statistic. *Family Medicine*, 37(5), 360-363.

Waldron, M. & Highton, J. (2014) Fatigue and pacing in high-intensity intermittent team sport: an update. *Sports Medicine*, 44(12), 1645-1658.

Waldron, M., Harding, J., Barrett, S. & Gray, A. (2020) A new foot-mounted inertial measurement unit system in soccer: reliability and comparison to global positioning systems for velocity measurements during team sport actions. *Journal of Human Kinetics*, 77(1), 37-50.

Waldron, M., Worsford, P., Twist, C. & Lamb, K. (2011) Concurrent validity and test-retest reliability of a global positioning system (GPS) and timing gates to assess sprint performance variables. *Journal of Sports Sciences*, 29(15), 1613-1619.

Walker, E., McAinch, A., Sweeting, A. & Aughey, R. (2016) Inertial sensors to estimate the energy expenditure of team-sport athletes. *Journal of Science and Medicine in Sport*, 19(2), 177-181.

Walker, G. & Hawkins, R. (2018) Structuring a program in elite professional soccer. *Strength and Conditioning Journal*, 40(3), 72-82.

Wallace, J. & Norton, K. (2014) Evolution of World Cup soccer final games 1966-2010: game structure, speed and play patterns. *Journal of Science and Medicine in Sport*, 17(2), 223-228.

Wallace, L., Slattery, K. & Coutts, A. (2014) A comparison of methods for quantifying training load: relationships between modelled and actual training responses. *European Journal of Applied Physiology*, 114(1), 11-20.

Wang, Y., Zhao, Y., Chan, R. & Li, W. (2018) Volleyball skill assessment using a single wearable micro inertial measurement unit at wrist. *Institute of Electrical and Electronics Engineers Access*, 6(1), 13758-13765.

Ward, P., Windt, J. & Kempton, T. (2019) Business intelligence: how sports scientists can support organisation decision making in professional sport. *International Journal of Sports Physiology and Performance*, 14(4), 544-546.

Wass, J., Mernagh, D., Pollard, B., Stewart, P., Fox, W., Parmar, N., Jones, B., Kilduff, L. & Turner, A. (2020) A comparison of match demands using ball-in-play vs. whole match data in elite male youth soccer players. *Science and Medicine in Football*, 4(2), 142-147.

Weaving, D., Beggs, C., Dalton-Barron, N., Jones, B. & Abt, G. (2019) Visualising the complexity of the athlete monitoring cycle through principal component analysis. *International Journal of Sports Physiology and Performance*, 14(9), 1304-1310.

Weaving, D., Jones, B., Till, K., Marshall, P. & Abt, G. (2017) Multiple measures are needed to quantify training loads in professional rugby league. *International Journal of Sports Medicine*, 38(10), 735-740.
Weston, M. (2018) Training load monitoring in elite English soccer: a comparison of practices and perceptions between coaches and practitioners. *Science and Medicine in Football*, 2(3), 216-224.

Weston, N., Greenlees, I. & Thelwell, R. (2011) Athlete perceptions of the impacts of performance profiling. *International Journal of Sport and Exercise Psychology*, 9(2), 173-188.

White, A., Hills, S., Hobbs, M., Cooke, C. Kilduff, L., Cook, C., Roberts, C. & Russell, M. (2020) The physical demands of professional soccer goalkeepers throughout a week-long competitive microcycle and transiently throughout match-play. *Journal of Sports Sciences*, 38(8), 848-854.

Whitehead, S., Till, K., Weaving, D. & Jones, B. (2018) The use of microtechnology to quantify the peak match demands of the football codes: a systematic review. *Sports Medicine*, 48(11), 2549-2575.

Williams, A. (2000) Perceptual skill in soccer: implications for talent identification and development. *Journal of Sports Sciences*, 18(9), 737-750.

Williams, A. & Ford, P. (2008) Expertise and expert performance in sport. *International Review of Sport and Exercise Psychology*, 1(1), 4-18.

Williams, A. & Hodges, N. (2005) Practice, instruction and skill acquisition in soccer: challenging tradition. *Journal of Sports Sciences*, 23(6), 637-650.

Williams, A. & Reilly, T. (2000) Talent identification and development in soccer. *Journal of Sports Sciences*, 18(9), 657-667.

Williams, A. & Ward, P. (2007) Anticipation and decision making: exploring new horizons. In Tenenbaum, G. & Eklund, R. (eds) *Handbook of sport psychology*. Hoboken: Wiley, 203-223.

Williams, A., Hodes, N., North, J. & Barton, G. (2006) Perceiving patterns of play in dynamic sport tasks: investigating the essential information underlying skilled performance. *Perception*, 35(3), 317-332.

Williams, J. (2012) Operational definitions in performance analysis and the need for consensus. *International Journal of Performance Analysis in Sport*, 12(1), 52-63.

Wilson, C., Simpson, S., Van Emmerik, R. & Hamill, J. (2008) Coordination variability and skill development in expert triple jumpers. *Sport Biomechanics*, 7(1), 2-9.

Wilson, R., Plumley, D., Mondal, S. & Parnell, D. (2020) Challenging parachute payments and unmasking English football's finances. *Managing Sport and Leisure*, online ahead of print.

Wilson, R., Ramchandani, G. & Plumley, D. (2018) Parachute payments in English football: softening the landing or distorting the balance. *Journal of Global Sport Management*, 3(4), 351-368.

Wisdom, K., Delp, S. & Kuhl, E. (2015) Use it or lose it: multiscale skeletal muscle adaptation to mechanical stimuli. *Biomechanics and Modelling in Mechanobiology*, 14(2), 195-215.

Wright, C., Atkins, S. & Jones, B. (2012) An analysis of elite coaches' engagement with performance analysis services (match, notational analysis and technique analysis). *International Journal of Performance Analysis in Sport*, 12(2), 436-451.

Wright, C., Atkins, S., Jones, B. & Todd, J. (2013) The role of performance analysts within the coaching process: performance analysts survey 'the role of performance analysts in elite football club settings'. *International Journal of Performance Analysis in Sport*, 13(1), 240-261.

Wright, C., Carling, C. & Collins, D. (2014) The wider context of performance analysis and its application in the football coaching process. *International Journal of Performance Analysis in Sport*, 14(3), 709-733.

Wright, C., Carling, C., Lawlor, C. & Collins, D. (2016) Elite football player engagement with performance analysis. *International Journal of Performance Analysis in Sport*, 16(3), 1007-1032.

Yarrow, D. & Kranke, M. (2016) The performativity of sports statistics: towards a research agenda. *Journal of Cultural Economy*, 9(5), 445-457. Yi, Q., Gómez-Ruano, M., Liu, H., Zhang, S., Gao, B., Wunderlich, F. & Memmert, D. (2020) Evaluation of the technical performance of football players in the UEFA Champions League. *International Journal of Environmental Research and Public Health*, 17(2), 604-616.

Yi, Q., Groom, R., Dai, C., Liu, H. & Gómez-Ruano, M. (2019) Differences in technical performance of players from the 'big five' European football leagues in the UEFA Champions League. *Frontiers in Psychology*, 10(1), 1-8.

Zeederberg, C., Leach, L., Lambert, E., Noakes, T., Dennis, S. & Hawley, J. (1996) The effect of carbohydrate ingestion on the motor skill proficiency of soccer players. *International Journal of Sport Nutrition and Exercise Metabolism*, 6(4), 348-355.

Zhou, Q., Zhang, H., Lari, Z., Liu, Z. & El-Sheimy, N. (2016) Design and implementation of footmounted inertial sensor based wearable electronic device for game play application. *Sensors*, 16(10), 1752-1776.

Zubillaga, A., Gorospe, G., Hernandez, A. & Blanco, A. (2009) Comparative analysis of the highintensity activity of soccer players in top level competition. In Reilly, H. & Korkusuz, F. (eds) *Science and football VI*. London: Taylor and Francis Group, 182-185.