THE IMPLEMENTATION OF DATA SCIENCE IN FOOTBALL

This dissertation is submitted for the degree of

Doctor of Philosophy

By

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Roll the Dice
by Charles Bukowski

If you're going to try, go all the
way.
Otherwise, don't even start.

If you're going to try, go all the
way. This could mean losing girlfriends,
wives, relatives, jobs and
maybe your mind.

Go all the way.
It could mean not eating for 3 or
4 days.
It could mean freezing on a
park bench.
It could mean jail,
it could mean derision,
mockery,
isolation.
Isolation is the gift,
all the others are a test of your
endurance, of
how much you really want to
do it.
And you'll do it
despite rejection and the
worst odds
and it will be better than
anything else
you can imagine.

If you're going to try,
go all the way.
There is no other feeling like
that.
You will be alone with the
gods
and the nights will flame with
fire.

Do it, do it, do it.
Do it.

All the way
all the way.
You will ride life straight to
perfect laughter,
it's the only good fight
there is

Declaration

I, Mat Herold, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, at the Institute of Sport and Preventive Medicine, Saarland University.

This thesis is completely my own work as the sole author unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This thesis is the result of a Doctoral Research Degree program with the Institute of Sport and Preventive Medicine, Saarland University=.

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Mat Joseph Herold　　　　Date:

Mat Herold　　　　18-10-2022

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I have always had a difficult time making big life decisions. When deciding whether to embark on the PhD journey in Germany, I had a few days to think about it but ultimately, I never decided for myself. It was decided for me when Professor Meyer said to me on a follow up Skype call, “I just need a ‘probably yes’”. I echoed immediately, “probably yes”. And so, it began.

Living in Europe and being immersed into a competitive cauldron of athletic-minded academics was both provocative and comforting at the same time. Sitting in the PhD breakfast meetings and listening to everyone’s progress, and sometimes lack thereof, was daunting. I had a mountain of work and problem solving ahead of me. Yet, each PhD student was incredibly supportive and willing to help. The conversations were very stimulating, and I found each PhD colleague could discuss subjects at depth and embraced friendly debates on a variety of topics.

Nonetheless, I spent the first-year questioning whether I had any business doing a PhD. “I am a coach, what am I doing all this for?”, I would think. But the overall experience was so captivating and the integration of myself with enthusiastic and tactically astute World Cup winners such as Stephan Nopp and Christofer Clemens at the DFB kept me going. Along the way I was met with scientific difficulties, interpersonal conflicts, getting extremely sick a few times in the first year because I didn’t read German meat labels, and many other ups and downs.

In retrospect, it is much easier to be grateful for all the challenging encounters and experiences along the way. To Tim Meyer, thank you for being decisive and getting me to say, “probably yes”. I am grateful you held me to the standard of doing an intervention study despite my attempts to convince you otherwise. It forced me to get creative and network with companies, to become a better scientist, and see the game of football in a new way. Mostly I am thankful for the overall opportunity to live in your charming city of Saarbrucken, feel a part of the Institute, and build friendships with like-minded people.

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In loving memory of my mom, Marcia Botwin Herold. Completing this took every bit, and still only a shade of her feistiness and determination.

List of Publications Incorporated into This Thesis

The below list outlines the published, in press or in preparation studies that are incorporated into this thesis. The studies listed below are presented in full in the following Chapters of this thesis.

Chapter 3:

i. Herold M, Goes F, Nopp S, Bauer P, Thompson C, Meyer T. Machine learning in men's professional football: Current applications and future directions for improving attacking play. International Journal of Sports Science & Coaching. 2019;14(6):798-817. https://doi.org/10.1177/1747954119879350

Chapter 4:

i. Herold, M., Kempe, M., Bauer, P., & Meyer, T. (2021). Attacking Key Performance Indicators in Soccer: Current Practice and Perceptions from the Elite to Youth Academy Level. Journal of sports science & medicine, 20(1), 158–169. DOI:10.52082/jssm.2021.158

Chapter 5:

i. Herold M, Hecksteden A, Radke D, Goes F, Nopp S, Meyer T, Kempe M. Off-ball behaviour in association football: A data-driven model to measure changes in individual defensive pressure. J Sports Sci. 2022 May 31:1-14. DOI: 10.1080/02640414.2022.2081405

Chapter 6:

i. HEROLD, M., KEMPE, M., RUF, L., GUEVARA, L. & MEYER, T. 2022. Shortcomings of applying data science to improve professional football performance: Takeaways from a pilot intervention study. Frontiers in Sports and Active Living, 4 doi:10.3389/fspor.2022.1019990

Preface

This dissertation is the collaboration of research that combines early traditions of measuring football performance with the most recent findings that scientists have made with advances in technology. It is my hope that this contribution connects the different domains of research and practice to help improve football and science in football. This thesis should present a clear synergy of the research and presents the findings in a way that is actionable for both researchers and practitioners.

I wrote this thesis and all the manuscripts included around the world from Europe to the United States. Football is the world's game, and it seems fitting that my doctoral experience allowed me to travel and live internationally. As my research evolved, so did my understanding and awareness about different philosophies and cultures around the sport as well as approaches to science.

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List of Symbols and Standard Abbreviations

ANOVA	Analysis of Variance
Au	Arbitrary Units
Bundesliga	Germany's 1st division in football
C	Congruent
Cev	Conditional Explained Variance
CI	Confidence Intervals
COD	Change of direction
CV	Coefficient of Variation
D-Def	Defensive disruptiveness caused by a pass
ES	Effect Size
Exp	Years of experience playing football
F	F-Value
Football	Association Soccer
Hz	Hertz
IMU's	Inertial Measurement Units
IQR	Interquartile Range
Km/hr	Kilometres per hour
m	Meters
MANVOA	Multivariate Analysis of Variance
ms	milliseconds
NOO	Number of Outplayed Opponents
n	Number of participants
P	P-Value
r	Pearson's Correlation
RM-MANOVA	Repeated Measures Multivariate Analysis of Variance
%	Percentage
SOG	Shots on Goal
Xg	Expected Goals

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Abstract

The interaction between technical, physical, and tactical aspects of play determine success in association football (soccer). While each of these factors have been researched extensively, the explosion of sports analytics including the use of data science, has opened the door to new possibilities. On a play-by-play basis, football players must make rapid decisions that fit the paradigm of the coaches' game plan. To successfully guide individual and team tactics, the coaching staff need to prepare for each opponent based on their strengths and weaknesses as well as their own. Historically, this has been done with notational analysis of rudimentary statistics known as *event data* to answer simple questions such as how many passes have been completed or of all the shots taken, how many of them have been on target. Nowadays, because of advances in technology, a new type of data knowns as *tracking data*, also referred to as positional data, has become increasingly available. Via local or global positioning systems (LPS/GPS), or through computer vision algorithms, positional tracking data captures the positions of all players and often the ball, at up to 25 Hz per second. Given the speed and complexity of tactical play, and the difficulty in quantifying these dynamics, positional tracking data provides an understanding of not only what occurred, but the process behind key events. Taking a dynamic systems approach to tactical analysis, this thesis aimed to increase the understanding of the capabilities of data science to evaluate and improve football performance. To fulfil this aim, a series of four studies were completed.

Study 1, a narrative review of literature investigating machine learning assisted quantification of tactical play, showed that passing behaviour of football players has been examined extensively, but that most of the research lacks in practical application and data scientists keep focusing on new metrics instead of improving existing ones. As a result, there is not a clear understanding of how to integrate data driven metrics into practice during actual football training and match-play. Further, the reliance on data science and machine learning approaches for purposes of prediction has resulted in experimental designs that lack in practical application for coaches and analysts. This is problematic in that the machine learning algorithms need further refining and the gap between the aims of researchers and the needs of practitioners needs narrowing. The narrative review of literature showed that there is a need to simplify the metrics and make them more process orientated to improve transferability to the pitch.

Study 2 surveyed staff members across various levels in multiple countries to determine the use and the value they find in various key performance indicators. This included an explicit assessment of twelve attacking KPIs. The findings indicate that the level of play determines how practitioners implement KPI and there was an obvious preference for simpler metrics related to shots. The low perceived value of positional tracking data driven KPIs was explained by low buy-in that can be improved with better education and collaboration between data scientists and practitioners.

Study 3 expanded on Studies 1 and 2 by exploring off-ball behaviour, an area of football that could add value to the coaching process but is currently understudied. A defensive pressure model was adapted from an earlier on-ball pressure model to examine an offensive player's ability to create separation from a defender using 1411 high-intensity off-ball actions including 988 Deep Runs (DRs) DRs and 423 Changes-of-Directions (CODs). The effectiveness of the pressure model was validated by discovering defensive pressure on the receiver at the moment of the pass was lower for completed passes than incomplete passes. Greater starting pressure on the attacker player generally led to greater subsequent decreases for DRs and CODs. There were also differences between offensive and defensive positions and the number of off-ball actions.

Study 4 represented the first study to investigate the implementation of positional tracking data to improve football performance during 11v11 match-play. Using professional football players midseason, results showed the two chosen data driven metrics, D-Def and Number of Outplayed Opponent (NOO), did not significantly improve for the intervention team. However, the traditional metrics based on notational analysis such number of passes, penalty box entries, and shots on goal penalty box entries, did show greater numerical increases demonstrating a general positive outcome from the video intervention, these findings suggest future studies should aim to include a lengthier intervention that includes collaborative efforts with coaches to design training exercises that encourage behaviors that match the chosen metrics.

Together, the findings supported the theoretical basis of the thesis, such that the use of positional tracking data can assist in the discovery and developmental process of tactical play. In addition, the findings provide some insight into the constraining factors on the use of positional tracking data in football. The findings have important implications for research methodology and applied practice. By quantifying a player's effectiveness when they do not have the ball, coaches are equipped with a unique way of providing feedback to such an important part of the game. Further, the novel use of positional tracking data to quantify off-ball behaviour as well as passes throughout this thesis shows the value of these methods for future investigations, especially in the ability to quantify process orientated aspects of play. While this thesis contains limitations in the design, the theoretical underpinnings, methodology, and findings of this thesis provide a platform for future investigations involving positional tracking data in football.

Navigation of Thesis

Tactical analysis is a crucial component of coaches and analysts' preparation for training and matches. Advances in technology, including positional tracking data, have opened the door for new ways to quantify performance and inform practitioners about not only what happened on the pitch, but how it happened. Despite this, it is a relatively new field and there is a disconnect between football-related data science research and the needs of practitioners. This thesis addresses this disparity in a multitude of ways: a review on what has been done, a survey to discover what needs to be done, an experimental study on an area in which data science has generally missed, and an intervention study to see what works and what doesn't when implementing tracking data in a practical setting to improve performance.

Chapter 1 provides a general introduction to the thesis, including a historical and theoretical description of tactical analysis.

Chapter 2 provides a statement of problems and related aims of the experimental studies within this thesis.

Chapter 3 provides a narrative review of the extant literature which has used machine learning approaches to investigate tactical behaviour in football. The intent is to provide the reader with an introduction to machine learning including an explanation how supervised and unsupervised learning differ in a football context. Further, we discuss problems associated with this area of research and identify areas of need to improve the transferability from science to practice.

Chapter 4 surveys practitioners across a range of roles and levels of competition in different countries for their use and perceived value of various key performance indicators (KPIs).

Chapters 5 and 6 examine the use of data driven approaches to evaluate and improve aspects of football performance, respectively. The intent of these chapters is to further examine the use of positional tracking data in 11v11 match-play, making use of various models to quantify the off-ball behaviour and passing performance of football players. Chapter 5 investigates an adapted pressure model to determine the relationship between off-ball behaviour and changes in defensive pressure. Chapter 6 investigates how a video intervention consisting of clips derived from positional tracking data improve passing performance on a professional football team. Chapter 7 provides a general discussion of the thesis, including a summary of findings, an overview of the major contributions to theory, methodology and applied practice, and research strengths and limitations.

Chapter 1: General Introduction

"The objective is to move the opponent, not the ball."

— Pep Guardiola

The quote above, stated by the current Manchester City football club manager, Pep Guardiola, is a basic introduction to the aim of this dissertation. From a tactical perspective, this thesis will explore how football teams create goal-scoring chances. More specifically, we will discuss the utilization of data science for attacking play in football.

Tactics in football is a term associated with the strategy. A strategy can be defined as the attempt to limit the effects of any weaknesses while optimizing an individual and team's strengths in a plan established prior to competition (O'donoghue, 2009). Tactics are considered "residual choices" available to the player or team based on the strategy they chose to adopt (Casadesus-Masanell & Ricart, 2010). In football, match statistics and video footage of training and competition are often used to assess one's performance and prepare for upcoming opponents. This process, known as *match analysis,* contributes to performance by informing decisions based on objective feedback (Christopher Carling, Williams, & Reilly, 2007).

"Football is not about players, or at least not just about players; it is about shape and about space, about the intelligent deployment of players, and their movement within that deployment."

— Jonathan Wilson, Inverting the Pyramid: The History of Football Tactics

To truly understand tactics, or the X's and O's, we should first consider a country's historical, cultural, musical, and economic influences. Germany, esteemed for their *Kampfgeist*, or fighting spirit, played for years with a workmanlike, clinical style of play analogous to their business culture of the organisation, planning, and perfectionism. English football has often been characterized by comradery and courage, a stronghold of 19th-century conception of the game. The elite public schools in England coveted military virtues and projected them onto forms of violent folk football to groom future soldiers. The first football was introduced in Brazil in 1894 by Charles Miller, a descendant of British migrants who encountered football during his education in England. Football in Brazil was originally only played by the white elite, but with time, the poor and the afro-descendants started to participate more in the game. Historian, teacher, and Brazilian writer Joel Rufino wrote in the article *Bola Brasilis* published in the collective textbook *Brazil Bom de Bola*:

"…around the 1900s, the Brazilian people had nothing. They only had their body and the street. When the authorities managed to eradicate [or suppress] capoeira, around the 1900s, the people adopted soccer. Is capoeira Ginga? Let us play soccer with Ginga. Is capoeira dribbling? Let us make the dribble our main move."

Led by the athletic and imaginative Pele and Garrincha, Brazilian football did not follow Anglo-Saxon pragmatism; instead, it cultivated a less restricted, creative style of play. Brazil's playful style led to triumph in the 1958, 1962 and 1970 World Cups. Fundamentally, while Brazil incorporates its love of dance into football, the Italian style, much like their Colosseum or the Florence Cathedral, combines deliberate structure and aesthetics. The Italians, known for their *catenaccio* or "door bolt", rely on precise counterattacks from the fortress of their organized defense. However, not everyone accepts the stereotype that the tactical approach to football reflects the cultural characteristics of a country. German scholar Andrei Markovitz argues that it is not so simplistic. To Markovitz, the cultural explanation is too "facile and convenient," and that "national characteristics of any meaningful longevity do not exist". Further, he states it is unlikely the cultural changes that do occur manifest themselves on the pitch. Markovitz argues that the highly defensive *catenaccio* conflicts with the Italian reputation for being carefree and spontaneous. According to Markovitz, the "total football" displayed by the Dutch in the 1974 World Cup centered more on the philosophy of coach Rinus Michels and the qualities of players like Johan Cruyff and Johan Neeskens than any cultural reasons.

Perhaps, Markovitz is correct and tactical play is determined by factors other than cultural factors. After some frustrating performances in 2007, Sir Trevor Brooking, the director of development at the Football Association at the time, said that England's youth players were not learning technical skills early enough. *"We gave the ball away too much, and then we had to work so hard to get it back." "We need to start earlier," Brooking told BBC Sport. "Anybody emerging from the 5-11 age group has to be comfortable on the ball."* This realization led to the launching of the FA Skills Programme, led by Brooking and England midfielder Frank Lampard. They employed 66 qualified coaches who began visiting schools and clubs across the country to develop more technical skills at younger ages. The plan worked, as England made the semi-final of the 2018 World Cup and nowadays, English National Team players such as Phil Foden and Jack Grealish are as well equipped with skill and flair as their peers in Brazil or Spain.

Besides the impact of coaching and education, another possible influence on tactical play is the diversity created by global internationalization that has been transferred to football (Lanfranchi & Taylor, 2001). In the 2010 World Cup Final, Spain played a style more reminiscent of total football while the Dutch resembled the Catenaccio of the Italians. The origins align with Cruyff having been a key player and eventually an influential coach at FC Barcelona. Nonetheless, research on the effects of diversity in football has shown mixed results. Cultural diversity negatively affects team performance in the five largest European football leagues (England, France, Germany, Italy, and Spain) (Maderer, Holtbrügge, & Schuster, 2014). However, a more recent study proceeded to statistically separate talent based on price and salary (Ingersoll, Malesky, & Saiegh, 2017). In addition, the authors analysed the UEFA Champions League, where many teams have similar financial resources. Their results revealed that a diverse pool of players is beneficial to performance. Further, it is common nowadays for players to play for clubs outside of their home country, and the variability of tactics and skills players are exposed to adds to their tactical diversity. Roberto Martínez, the manager of the Belgium National Team since 2016, concurs, “I think that diversity is probably the biggest weapon that we have in our dressing room. You always get different views and different solutions. You're very aware at a young age that in life you can do things in many, many ways; that is the way that you face adversity.”

In summary, as the world changes, football also evolves, and numerous factors have influenced the game over the years. One of the influential factors has included scientific research. In 1968, Reep and Benjamin pioneered annotating data from professional football matches, inspiring further investigation of tactics and strategy. However, times have changed; nowadays, technology and big data are introduced into the footballing world with multiple HD cameras, enabling researchers and practitioners to develop new metrics and simplify the game into greater detail than ever before. This chapter will show that coaches use tactical analysis to determine how to approach the next match. This thesis contends that advances in technology, such as positional tracking data and machine learning (using algorithms and statistical models to analyze and draw inferences from patterns in data), will control data collection and analysis in the future. However, there are major gaps between data science and the status quo in tactical analysis in football. This is an oversight that this thesis aims to overcome. In the remaining sections of the general introduction, an explanation of tactical analysis in football is provided based on notational analysis, which then transitions into early findings using positional tracking data. The thesis then reviews research done using machine learning in football, followed by an investigation of what key performance indicators coaches use and value. Next, we provide an example of the sort of analysis possible using positional tracking data as we examine off-ball behavior. Finally, we make a first-known attempt to bridge the gap between data science and football to elicit improved passing performance.

1.1 Theoretical Background: The Use and Usefulness of Match Analysis

Association Football is an invasion team sport played by two teams of 11 players on an ~110m by ~75m pitch (International Football Association Board, 2017). The 22 players are free to move anywhere on the pitch, which results in highly dynamic movement between players as teams form numerical superiority to create goal-scoring opportunities (Hewitt, Greenham, & Norton, 2016). Due to these complex interactions, the flow of play in football is unpredictable, which requires each player to have a constant understanding of their teammates' locations, roles, and abilities to successfully execute the team's strategy.

As previously mentioned, the game of football is constantly evolving. Elite football demands high levels of versatility and motor ability, as well as rapid information processing and decision-making (Wallace & Norton, 2014). Evidence from both the English Premier League (2006-2013) and the FIFA World Cup (1966-2010) show that in addition to more matches being played than before, more distances are being covered at high-speed, and there are a greater number of technical actions per match (Barnes, Archer, Hogg, Bush, & Bradley, 2014; Nassis et al., 2020). From 1966 to 2010, a pattern of space management emerged, with teams increasing the density of players in a defense posture (Wallace & Norton, 2014). More players organized behind the ball forced teams to expand their attacking arsenal. As such, match analysis has increasingly gained greater interest in quantifying and qualifying indicators that can influence and predict future performance (O'Donoghue, Papadimitriou, Gourgoulis, & Haralambis, 2012; O'Donoghue et al., 2005).

While critical events such as goals and controversial decisions are often easily remembered, non-critical events are likely to be forgotten or clouded by personal bias and the emotional state of coaches and analysts (Mike Hughes, 2015). The ability to recall only selected portions of the match, referred to as *highlighting*, distorts the coach's perception of the performance (Mike Hughes & Franks, 2008). By notating events, such as the pass completion rate of midfielders or the number of blocked shots by a defender, analysts can provide specific information to coaches and a complete perspective about the players and team.

Hughes (2004) defined notational analysis as "a procedure that could be used in any discipline that requires assessment and analysis of performance"(Mike Hughes, 2004). In the last two decades, the combined use of high-speed video cameras with video analysis software such as Opta and Sportscode allowed faster processing speeds. It offered a wide range of features and tools to analyse performance. Software companies (i.e., Sportec Solutions AG) now collect leaguewide event data and provide them to each team (Lucey, Oliver, Carr, Roth, & Matthews, 2013). Since 2006, global positioning system (GPS) technology has been used to detect fatigue, determine the intensity, and inform practitioners with precise movement profiles (Aughey, 2011). The integration of technologies consisting of GPS and heart rate combined with event data has led to detailed analyses of many aspects of the game, such as the importance of team tactics and the opponent's style of play and their impact on physical demands (Castellano, Alvarez-Pastor, & Bradley, 2014). However, no common framework exists for measuring performance, and each team must determine how to interpret the wide range of information gathered by notational analysis. For example, one team may value the number of shots on target, while another team may disregard that statistic in favour of possession in the opposition's final third. Similar discrepancies exist in measuring and monitoring physical performance in elite football (Akenhead & Nassis, 2016). Accordingly, a body of research using GPS and other technologies have explored how various physical parameters relate to performance.

1.2 Match Analysis and Physical Performance

Physical performance has been the focus of several studies on match analysis. For example, at the elite youth level, greater muscle mass and lower body fat percentage were found in players from successful teams compared to unsuccessful teams (Carlos Lago-Peñas, Casais, Dellal, Rey, & Domínguez, 2011). In the English Premier League, first-team players had greater lean mass than U-18 and U-21 players (Milsom et al., 2015) and differences in strength and power measures have been found between elite and amateur players (Arnason et al., 2004; Wisloeff, Helgerud, & Hoff, 1998). These findings suggest a focus on optimal nutrition and strength training for increased performance and injury prevention which is common practice in most clubs and academies (Read, Jimenez, Oliver, & Lloyd, 2018). However, since GPS can measure various distance-related metrics, researchers and practitioners have been focused on those metrics to monitor workloads and find correlations between distances covered at varying intensities and tactical performance.

The research regarding the significance of running at varying intensities as a determinant of match success is contradictory. Professional players cover an average of 10–13 km during a match, but most distance is covered by walking and low-intensity running (Bangsbo, Iaia, & Krustrup, 2007; Di Mascio & Bradley, 2013). Studies have shown that high-intensity actions, including high-speed running and sprinting, distinguish top players from those competing at lower levels (Mohr, Krustrup, & Bangsbo, 2003). However, in conflicting results, top Italian teams covered less (4–12%) high-intensity running distance than unsuccessful teams, but more distance while in possession of the ball (Rampinini, Impellizzeri, Castagna, Coutts, & Wisløff, 2009). Better teams (in some leagues) can adopt a pacing strategy and are more selective about expending energy, waiting for the right moments to exert themselves. In contrast, competing against superior opponents is associated with lower ball possession and greater distances covered, likely in the effort to regain possession (Bloomfield, Jonsson, Polman, Houlahan, & O'Donoghue, 2005; C Lago-Peñas, Rey, Lago-Ballesteros, Casais, & Dominguez, 2009). Carling et al. (2013) found that lower-ranked teams covered greater high-speed running distances, and total distances were not associated with results in the 2010 World Cup or the 2014 World Cup (Christopher Carling, 2013). Combined with other studies, these results suggest that factors other than physical performance are more important in achieving success

in a football match (Janković, Leontijević, Jelušić, Pašić, & Mićović, 2011; Rumpf, Silva, Hertzog, Farooq, & Nassis, 2017).
In conclusion, although the ability to repeat high-intensity actions is an important aspect of performance in football, covering greater distances does not guarantee success. Numerous factors, weather, field surface, opponent quality, technical ability, etc., affect the distances covered at varying intensities in a game (Paul, Bradley, & Nassis, 2015). Therefore, coaches must consider these factors when determining tactical strategy and identifying players to fulfil specific roles.

1.2.1 Influence of Tactics on Physical Performance

Tactical components such as team formation, style of play, and playing position all place unique demands on the individual players. For instance, investigating physical output on a team level has shown that the team's playing formation affects the amount of high-intensity running performed by attacking players (Bradley et al., 2011). Central defenders typically cover less total distance and perform less high-intensity running than players in other positions, probably related to their tactical roles and lower endurance capacity (Krustrup et al., 2003; Mohr et al., 2003). Unsurprisingly, midfielders cover the greatest distances while forwards and wide midfielders cover the greatest high-speed running distances (Dellal et al., 2011). In the English Premier League, high-speed running and sprint distance significantly declined during the second half, with the greatest decrements observed in wide midfield and attacking players (Di Salvo, Gregson, Atkinson, Tordoff, & Drust, 2009).

In general, differences between players within the same position and between different positions are dependent on playing style and formation (Christopher Carling, 2011). For example, in a 4-5-1 formation, players cover more high-intensity and sprint distance than in a 3-5-2 formation (Baptista, Johansen, Figueiredo, Rebelo, & Pettersen, 2019). Another recent study on playing formation and running intensities found that playing with three defenders led to higher sprint distances among center backs and fullbacks compared to all other formations involving four defenders (Leon Forcher et al., 2022). However, players in a 4-5-1 formation perform less very-high-intensity running when their team is in possession and more when their team is out of possession compared to the 4-4-2 and 4-3-3 formations. Perhaps this is because of the higher density of players in the midfield shape of a 4-5-1 compared to the 4-4-2 and 4-3-3. Besides attackers in a 4-3-3 performing about 30% more high-intensity running than attackers in the 4-4-2 and 4-5-1 formations, there was little difference between positions. The authors concluded that formation influences very high-intensity running activity for all positions with the greatest impact on the movement profile of attackers. However, comparing different formations, including 4-4-2, 4-3-3 and 4-5-1, no differences were observed in total distance covered or high-intensity running (Bradley et al., 2011).

1.3 The Interplay between Technical and Tactical Performance

Just as there is a complex interplay between tactics and physical performance, tactics and technical performance have their dynamic correspondence. A large body of research has investigated the technical and tactical aspects of the game (Ávila-Moreno, Chirosa-Ríos, Urena-Espa, Lozano-Jarque, & Ulloa-Diaz, 2018; Lepschy, Wäsche, & Woll, 2018; Sarmento et al., 2014). The results show that there are position-specific technical demands that change based on a team's chosen formation (Brito, Roriz, Silva, Duarte, & Garganta, 2017; Lovell, Bocking, Fransen, & Coutts, 2018; Yi, Jia, Liu, & Gómez, 2018) and the opposition team's formation. For example, a 4-4-2 formation demonstrated more successful passes than 4-3-3 and 4-5-1 formations (Bradley et al., 2011). Carling et al. (2011) discovered that there are significant differences in attacking and defensive patterns when competing against a 4-4-2, a 4-2-3-1, and a 4-3-3/4-5-1 (Christopher Carling, 2011). Against a 4-4-2, teams were more likely to control possession, and in the defensive and midfield areas of the field, players performed more passes and had more ball touches per possession. It is possible this occurrence was due to greater spaces left in the midfield by a 4-4-2 formation. In support of strength in the midfield, Clemente' et al. (2013) found that the attacking midfield zone was the main region that contributed most to goals scored and conceded (F. M. Clemente, Couceiro, Martins, & Mendes, 2013). This is supported by the findings from Carling (2011) that also showed the defensive superiority of 4-2-3-1, as the opposition were forced into considerably more duels (aerial and ground) and one-touch passes than when competing against a 4-4-2. The greater number of duels and higher frequency of one-touch passes against teams using a 4-2-3-1 formation suggests that attacking players are experiencing defensive pressure more rapidly and have less time on the ball to make a play.

In addition to different formations influencing technical and tactical functions, recruiting talented players who fit the tactical system and can make important plays is of the utmost importance. Analysing games from the 2008 UEFA European Championships, Duch et al. (2010) compared the performance of two teams, identified the players with the greatest impact, and extracted the overarching strategies and efficiencies of team play (Duch, Waitzman, & Amaral, 2010). Passing and shooting accuracy were key performance indicators to measure an individual player's effectiveness. Though losing the ball on a dribble could increase the chance for the opponent to counterattack, successful 1 versus 1 dribbling action unbalances the defense and may lead to scoring chances (Luhtanen, Belinskij, Häyrinen, & Vänttinen, 2001). Widely known for their individual talent, Brazil demonstrated superior 1 versus 1 play as they became FIFA World Cup champions in 1994 (Loy, 1994). Thus, European clubs pay top dollar for Brazilian players who are a fixture of top sides in almost every league on the continent.

Creativity, or "the ability to produce work that is both novel (i.e., unexpected, original) and appropriate (i.e., useful)" (Sternberg & Lubart, 1999), is especially important in 1v1 situations to create goal-scoring chances (Duarte, Araújo, Davids, et al., 2012). Unpredictable and explosive movements disrupt the distance and relative speed between the attacker and the defender, thereby creating more space for the attacker (Duarte et al., 2010). This also explains why sprinting is the most frequent action involved in goal-scoring actions (Faude, Koch, & Meyer, 2012), and one of the key attributes of the player creating the assisting pass is the use of high-speed dribbling (Faude et al., 2012). In similar findings, Castañer et al. (2016) (Castañer et al., 2016) analysed the motor skills used by Argentinian Lionel Messi, a record 7-time winner of the Ballon d'Or (World Player of the Year), before scoring a goal. It was discovered that a big part of his success is the use of unpredictable, rapid changes of speed while simultaneously turning or angling his body to beat defenders.

1.3.1 Team Tactical Analysis

Although it is acknowledged that top players have a large influence on play style and team success (Gréhaigne, Wallian, & Godbout, 2005), focusing the match analysis process exclusively on one player is not enough to explain the dynamic nature of football. In addition, successful plays and mistakes occur randomly, and the team consisting of the best players does not always win (Grehaigne, Bouthier, & David, 1997; Skinner & Freeman, 2009). Therefore, analysts and coaches prioritize understanding successful and unsuccessful tactical determinants of team performance (Adams, Morgans, Sacramento, Morgan, & Williams, 2013; Szwarc, 2004a). The next section reviews some of the primary areas of interest that have been covered by research on football using notational analysis.

1.3.1.1 Ball Possession

Ball possession is one of the most widely studied performance indicators in football with plenty of successful examples at single games or even whole competitions in both sides of the debate (whether having a greater average ball possession is linked to success or not). Early work on ball possession found that most goals occur after three passes or less (Bate, 1988; J Garganta, Maia, & Basto, 1997; Reep & Benjamin, 1968; Stanhope, 2001). These findings birthed "direct play", influencing coaches and teams to get the ball closer to the opponent's goal with fewer passes. However, upon closer examination, Hook and Hughes discovered that better goals per shot ratio resulted in success more than the direct approach. Moreover, they found that successful teams from the UEFA Champions League, FIFA World Cup, and UEFA European Championships established longer possession times than the unsuccessful teams and during longer possessions, teams produced significantly more shots (Hook & Hughes, 2001).

The role of ball possession became a topic of increasing interest and continued to be studied by Hughes and other researchers. After analysing the shooting data for successful and unsuccessful teams for different lengths of passing sequences in the 1990 FIFA World Cup finals, it was found that longer passing sequences produced more goals per possession than shorter passing sequences for successful teams (Mike Hughes & Franks, 2008). Further work from Casal et al. (2015) (Casal, Losada López, & Ardá Suárez, 2015) analysed the 2008 UEFA European Championship, discovering that a longer offensive phase predicts greater success. In a follow-up study on the final phases of the 2016 UEFA European Championship, Casal et al. (2017) found that greater possession in the middle offensive zone increased a team's chances of victory (Casal, Maneiro, Ardá, Marí, & Losada, 2017). In addition, the most successful teams in the FIFA World Cup 2010 realized more passes per match than other teams. The highest ball possession rating in the FIFA 2014 World Cup belonged to the eventual Champions, Germany (F. Clemente, 2012).

Studies on domestic competitions also found possession positively related to successful performance. Significant differences favoring possession between successful and unsuccessful teams were found in the English Premier League (N James, Jones, & Mellalieu, 2004; Jones, James, & Mellalieu, 2004). Bloomfield et al. (2005) (Bloomfield et al., 2005) showed that the top three teams in the 2003–2004 English Premier League achieved longer possession times than their opponents. In the Spanish league, Lago-Penas and Dellal (2010)(Carlos Lago-Peñas & Dellal, 2010) provided evidence to support the relationship between possession time and success. Moreover, an analysis of Barcelona FC's 2008/09 La Liga winning season further strengthened the case for possession as they registered the highest percentage of ball possession while scoring 105 goals during the 38 league matches(Carlos Lago-Peñas, Lago-Ballesteros, Dellal, & Gómez, 2010).

Longer time in possession seems to be a characteristic that separates successful teams from unsuccessful teams. However, for unsuccessful teams, greater time in possession does not seem to offer an advantage (Balyan et al., 2007). Perhaps this is because, as Hughes & Bartlett (2002) (M. D. Hughes & Bartlett, 2002) discovered that success with possession lies in overall technical ability relative to the opponent. In other words, the technical superiority of top teams allows them to control more of the game and make better use of their possession. To highlight this, a study conducted in the Italian Serie A found that teams in the top 5 standings had a greater number of short passes than teams in the bottom 5 positions (Rampinini et al., 2009). There were similar findings in the English Premier League, as passes on the ground into the final third were used more often by successful teams than unsuccessful teams who tended to rely more on aerial balls (Rees, James, Hughes, Taylor, & Vučković, 2010a). In addition, research from the Spanish La Liga found that possession time changes depending on the context of the match (Lago & Martín, 2007). The researchers found possession varied based on the quality of the opponent and was positively affected by playing at home and playing behind in the score line. The conflicting nature of the research highlights the fact that it may not be total possession that carries the most importance. Also, the negative aspects of losing ball possession (wrong/intercepted pass, failed dribbling, among others) have shown a positive relation with conceding goals (Shafizadeh, Lago-Penas, Gridley, & Platt, 2014). Thus, it is the effective usage of possession to create chances and score goals that distinguish successful and unsuccessful teams (Rees, James, Hughes, Taylor, & Vučković, 2010b).

1.3.1.2 Goal Scoring Patterns

In addition to possession and the types of possession that lead to scoring opportunities (to be discussed later), another area of interest in football research has been examining when goals occur. Understanding when goals most commonly occur can also provide useful information for decisions about training and specific match tactics. Illustrating the importance of an early goal, the team that scored first won 59.4 percent of the matches in the 2002 World Cup, 73.5 percent in the 1994 World Cup tournament, and 70.97% of the matches in the UEFA European Championships (Simiyu, 2014). Besides the importance of the early goal, studies have shown that performance during certain periods of a match has a greater impact on overall match outcome than others. Coaches and players can benefit from knowing that there is a greater likelihood of a goal occurring as the match progresses (Alberti, Iaia, Arcelli, Cavaggioni, & Rampinini, 2013; Armatas & Yiannakos, 2010). This trend occurs irrespective of the season or country, as it occurs in the English Premier League, the French Football League 1, the Italian Series A, and the Spanish Football League (Alberti et al., 2013).

One possible explanation is that physical fatigue (Bangsbo, 1994; Krustrup et al., 2006) and mental fatigue (Smith et al., 2016) accumulate throughout the match, thus increasing the occurrence of errors (Russell, Benton, & Kingsley, 2011). Furthermore, towards the end of the match, teams in need of a goal to either level the score line or take the lead tend to take greater risks using an "all-out offensive execution that may contribute to the higher proportion of goals in the last 15 minutes of matches" (Njororai, 2013). This combination of factors may explain the increased chance of scoring in each 15-minute interval of the match, with the highest likelihood of goals occurring in the final 15 minutes of each half.

1.3.1.3 Shooting Related Metrics

History has presented several football matches in which one team dominated possession and created more scoring chances but still lost. This section considers the significance of shooting efficiency. From the 2002 World Cup, Szwarc (2004) (Szwarc, 2004a) reported that champions Brazil, and finalists Germany, took on average only four more shots than less successful teams, but their shot effectiveness was three times greater. In the 2014 World Cup, Dufour et al. (2014) (Dufour, Phillips, & Ernwein, 2017) also distinguished between winning and losing teams and found that total possession, passing quantity, and passing quality were unrelated to team outcomes. Observed play patterns also had no significant impact on performance; shooting efficiency was related to success.

In addition to shooting efficiency, shots on target have been demonstrated to be one of the best metrics for separating successful and unsuccessful teams in top domestic leagues, such as the Italian Serie A (Rampinini et al., 2009) and the Spanish La Liga (Carlos Lago-Peñas et al., 2010). After looking for differences between winning, drawing and losing teams in three soccer World Cups (Korea/Japan 2002, Germany 2006 and South Africa 2010), the only variables that differentiated between successful and unsuccessful teams were total shots on target and shots on target received(Castellano, Casamichana, & Lago, 2012). The top two teams in the 2007-2008 Greek Soccer first division seasons had significantly more shots at goal than the bottom two teams (Armatas & Yiannakos, 2010), and in the 2012/2013 English premier league, the top ten teams had significantly more shots at goal than the bottom ten teams (Araya & Larkin, 2013). These studies add further evidence to support the importance of having a high number of shots on target (Grant & Williams, 1999; Muhamad, Norasrudin, & Rahmat, 2013).

Besides the number of shots or getting them on target, the chance quality determines the chances of scoring (Zengyuan Yue, Broich, & Mester, 2014). The quality of the chance is based on several factors: proximity to the goal and the amount of defensive pressure on the shooter. For instance, shots taken closer to the goal are more favourable than shots from a longer range and being more than one meter away from the nearest defender is related to higher conversion rates (Ensum, Pollard, & Taylor, 2004; Pollard, Ensum, & Taylor, 2004). Pollard also found that one-touch shots are more effective than when a player takes multiple touches to shoot, as one-touch shots lower the chances of the opponent anticipating and defending the shot. Similar results from a Serbian study suggest that taking more shots farther from the opponent's goal and allowing the opponent to take shots close to a team's own goal is correlated to losing (Janković et al., 2011).

More evidence in support of proximity to goal occurred after analysing all goals from one season in the English Premier League, with 87% being scored from inside the penalty area (Wright, Atkins, Polman, Jones, & Sargeson, 2011). An evaluation of winning Spanish teams (Gómez, Gómez-Lopez, Lago, & Sampaio, 2012) demonstrated they had more shots and goals inside the 6-yard box than drawing and losing teams. After analysing the 2012 European Championship, Armatas et al. (2014) (V. Armatas & R. Pollard, 2014) also identified a critical zone inside the penalty area from which most goals are scored. Despite only finding moderate correlations between scoring a goal and penalty box entries, Ruiz et al. (2013) (Ruiz-Ruiz, Fradua, Fernandez-Garcia, & Zubillaga, 2013) identified that losing teams in the World Cup allowed more entries into their penalty area compared to winning teams and that winning teams made more entries into their opponent's penalty area.

1.3.1.4 Qualitative Passing Analysis

It is important to recognize the value of getting into shooting ranges close to the opponent's goal. However, understanding how this can be achieved is even more important for coaches and analysts. Following notational analysis, key game events such as passes, shots, and goals have been recorded with little or no consideration given to temporal and specific match contexts. Moving away from quantitative analysis of ball possession, researchers began to explore what qualities constitute effective passing behaviour—starting in the early 2000s, match analysis expanded to detect play patterns of successful and unsuccessful teams by evaluating different variables such as shapes and distribution of passing patterns (Castellano-

Paulis, Hernández-Mendo, Morales-Sanchez, & Anguera-Argilaga, 2007; Fernandez-Navarro, Fradua, Zubillaga, Ford, & McRobert, 2016; Mike Hughes & Churchill, 2005; M. D. Hughes & Bartlett, 2002; Mackenzie & Cushion, 2013).

Passing accuracy is a crucial aspect of effective play, and a controlled approach with a higher percentage of short passes has been attributed to increased goal-scoring opportunities (Jones et al., 2004; Szwarc, 2004b). In support of a controlled approach, Redwood-Brown (2008) (Redwood-Brown, 2008) showed that the frequency of passes increases prior to a team scoring, and a team's passing frequency decreases before conceding a goal. To gain deeper insight into different attacking strategies, researchers used the software "MathBall" to analyze 676 games from the German Bundesliga 2009/2010, the 2010/2011 seasons, and the 2010 FIFA World Cup. An index of offensive behaviour (combines variables ball possession, number of passes, the mean time of an attacking sequence, the time between gain and loss of possession), an index of game control (passes per action, passing direction, and target player pass), and passing success rate and passing success in a forward direction, were generated. The index of offensive behaviour was able to distinguish between direct and possession-style play and make fine distinctions between the offensive approaches of different teams. Using the indexes, evidence revealed that possession play is linked with team success and the index of game control was the most important variable related to winning performance. Unique to these findings were that effective teams covered more ground per attack than weaker teams (Kempe, Vogelbein, Memmert, & Nopp, 2014).

Along with the frequency of passes and distances covered, another area of interest in the literature is the speed of the attack. For example, Lago-Peñas and Rey (2012) (J Lago-Ballesteros, Lago-Peñas, & Rey, 2012) discovered that in the Spanish La Liga, direct attacks and counterattacks were three times more effective than elaborate attacks of longer duration for producing a score box possessions. Collet (2013) (Collet, 2013) also supported speeding up the process of bringing the ball closer to the opponent's goal with fewer passes to reduce the opponent's time to respond. Supporting a balance between keeping possession and going forward with urgency, Nic et el. (2006) (Nic James, 2006) found that possession lengths of 3 to 7 passes are more likely to produce goals than shorter and longer length possessions. However, similar to the conflicting research on ball possession, evidence supports increased scoring situations for longer passing sequences lasting over 12 seconds (Albin Tenga & Sigmundstad, 2011). Moreover, Casal et al. (2015) (Casal et al., 2015) concluded that a longer offensive phase preceded greater success after analysing the 2008 UEFA European Championship. Perhaps there is a combination of temporal and sequential components associated with successful attacks, as Wright et al. (2011) (Wright et al., 2011) and Tenga and Sigmundstad (2011) (Albin Tenga & Sigmundstad, 2011) showed that shorter passing sequences involving one to four passes and long passing sequences involving five or more passes were both associated with more scoring situations.

To be effective, whether a passing sequence is elaborate or shorter in duration, the aim must be to disrupt the opponent's defensive structure as close as possible to the opposing goal (Collet, 2013). An analysis of goals in the German Bundesliga 2010-2011 season underscored the fact that besides possession or length of passes, the use of possession to create the most favourable shooting conditions possible carried the most value (Zengyuan Yue et al., 2014). However, Pratas et al. (2012) (Pratas, Volossovitch, & Carita, 2018) found that the quality of the opposition influences team strategy in the creation of scoring opportunities. To create shooting opportunities against stronger teams in the Portuguese Premier League, a high speed of ball movement and greater player movement in areas close to the opponent's goal are required. Tenga et al. (2010) (A. Tenga, Holme, Ronglan, & Bahr, 2010b) also found that the best chance of a "score box possession" or entering the opponent's penalty box with enough time to execute the attacking option varies depending upon the opponent's defensive setup. Although these findings reaffirm those of Rampini et al. (2009), they differ from Kempe et al. (2014) as they did not find teams to cover greater longitudinal distances in sequences ending with a shot on goal.

A combination of attacks featuring both short and long passes and short and long-range shooting attempts increases the defensive complexity for the opponent, which, in theory, can lead to more shots on goal (Oberstone, 2009). Kempe et al. (2014) and Tenga et al. (2010) demonstrated the importance of penetrating passes that achieve positional advantage over the opposition's defense to create scoring opportunities. Both long possessions starting in the attacking team's defensive third and penetrative passes have proven effective against a well-organized defense. Various attacks appeared to be successful against an imbalanced defense, including counterattacks and regaining possession in the defensive third of the opposition, also known as *counter-pressing* (a tactic discussed shortly), long possessions, long passes, and penetrative passes (A. Tenga et al., 2010b). In the first study on the combined effects of tactics and situational factors, Sarmento et al. (2018) (Sarmento, Clemente, Araújo, et al., 2018) examined their relationship to offensive outcomes in the four major European Football leagues (Germany, Spain, England, and Italy). Despite each country's unique style of play, counterattacks and fast attacks increased the probability of success by 40% compared with teams employing positional attacks of longer possession lengths.

1.3.1.5 Crossing

Teams cross the ball from different angles and ranges as a common strategy to score. Crossing the ball from wide areas into the penalty box has been identified as a valuable scoring strategy in several studies (Ensum et al., 2004; Mike Hughes & Churchill, 2005; Carlos Lago-Peñas & Dellal, 2010; Oberstone, 2009). In addition, crosses and short aerial "chip" passes were used more significantly by successful teams than unsuccessful teams (Mike Hughes & Churchill, 2005). Wide players who can serve an accurate crossed ball and strikers who can predict where the cross will land and are skilled at one-touch finishing are important for crossing to be effective (Ruiz-Ruiz et al., 2013). The effectiveness of crossing increases against a team poor at clearing the ball from the scorebox and goalkeepers with the propensity to mistime and drop aerial balls (Mike Hughes & Churchill, 2005). Further, the ability of the striker to lose their defender inside the box is also important; half of all goals scored in the UEFA European Championships were executed with low defensive pressure, and 43.7% of them were from crosses (Vasilis Armatas & Richard Pollard, 2014).

Although certain works favour crossed balls as an offensive tactic, an increase in scoring efficiency through crossed balls has been inconsistent (Flynn, 2001). In an analysis of teams from the English Premier League, German Bundesliga, and the FIFA World Cup 2014, Vecer et al. (2014)(Vecer, 2014) found that 1 out of 91.92 open-play crosses led to a goal. The crossing can also be risky due to the possibility of the opponent starting a counterattack after they clear the ball from their box into the midfield or after a goalkeeper intelligently and rapidly initiates an attack after a save. Vecer et al. (2014) concluded that a playing style based on crosses should be used by weaker teams playing against stronger teams with the hope of luck. He also argued for teams practicing their crossing and finishing sequences for a higher success rate.

Some of the most effective crosses with a higher probability of leading to a goal are cutback crosses, defined by UEFA (Union of European Football Association) as a pass back from near the goal line (Mitrotasios & Armatas, 2014; Yamada & Hayashi, 2015). According to the analytics company Opta, 19 of Manchester City's 66 goals in the 2018/2019 season, coached by Pep Guardiola, were scored from cutbacks inside the 6-yard box. However, cutbacks are hard to defend because once the attacking player is near the goal line, the defenders' vision becomes fixated on one side of the goal to view the ball. This makes it very difficult to identify which players (behind their backs) are free inside of the penalty box who might be open for a shot.

1.3.1.6 Counter Pressing

The success of Pep Guardiola at Barcelona, Bayern Munich, and now Manchester City has popularized a tactic known as the "5 second rule". The 5 second rule means that if a team is attacking higher up the pitch and loses the ball, the whole team must aggressively press the opponent and try to retain the ball in 5 seconds or less before retreating into a more compact, defensive shape closer to their own goal (Bell-Walker, McRobert, Ford, & Williams, 2006); (Mike Hughes & Lovell, 2019; Wright et al., 2011). Other teams such as Borussia Dortmund and Atletico Madrid, and coaches such as Jurgen Klopp, and the Deutscher Fussball-Bund (German Football Federation) have adopted similar philosophies to increase the speed at which players regain possession, thus stopping counterattacks before they start.

Denying the opponent chances to attack by regaining possession while they are in defensive zones is a key component to success in football (Christopher Carling, Reilly, & Williams, 2008). These methods are supported by other research, as the inability to regain possession appears to be one of the most important indicators of poor tactical behaviour (Kempe et al., 2014). An analysis of the type and zone of ball recovery in matches played in the 2011–2012 UEFA Champions League showed that better-ranked teams were more effective than worse-ranked teams in applying defensive pressure in more advanced pitch positions (Almeida, Ferreira, & Volossovitch, 2014). Defending closer to the opponent's goal is also supported by the review of Mackenzie and Cushion (2013) (Mackenzie & Cushion, 2013), who stated that regaining possession in the opponent's defensive third is one of the few aspects of defensive play related to success in football.

Regaining possession in the opponent's defensive area is not just a defensive preventative measure but a potential offensive tactic. Olsen and Larsson (1997) (Olsen & Larsen, 1997) showed that immediately after possession changed, the previous attacking team had an imbalanced defense, allowing more effective counterattacks by the opponent. In the 2002 World Cup finals, the winners (Brazil) had indices of possession gained in the opponent's defensive area, resulting in more attempts on high goal (S. Taylor, Ensum, & Williams, 2002). This is supported by the findings of Tenga et al. (2010), who reported that the chance of possession inside the opponent's penalty box decreases when there is a balanced defense. A greater number of goals were scored after regaining possession in the midfield third (Tenga et al., 2010; Tenga & Sigmundstad, 2011) and the opponent's defensive third (Gómez et al., 2012; Wright et al., 2011). Effectively, less skill is required to score goals against an unbalanced defense, especially when the attacks are initiated closer to the goal compared to being farther from the goal before high number of organized defenders (A. Tenga et al., 2010b).

Implementing a high-pressing defense leaves some coaches fearful about the potential risk of leaving space behind their defensive line or in their midfield if the team does not stay compact in the longitudinal plane. However, successful teams across European Leagues and in World Cups have higher attacking third regains, demonstrating that high-pressing may be worth the risk, after all (Bell-Walker et al., 2006; J Garganta et al., 1997).

1.3.2 The Rise of Positional Tracking Technology

All the previously mentioned work studying tactical play has involved the use of notational analysis to gather event data. Event data is limited in that it only provides information about *what* on-the-ball events occurred, and it does not provide information about *how* things occurred. Using multiple semi-automatic cameras, positional tracking data includes the position of every player and the ball (generally with a frequency of 10 or 25 Hz), providing a wider scope for tactical analysis across the whole pitch and not just limited to the player in possession (Borrie, Jonsson, & Magnusson, 2002; Stein et al., 2017). Based on the computer or data science, high volumes of complex data can be analysed, accompanied by detailed representations (Gudmundsson & Horton, 2017).

Positional data is acquired by either global or local positioning systems or optical tracking systems. As mentioned, GPS tracking data was predominantly used in sports science research for physical performance analysis (see Ravé et al. (2020) for an overview (Ravé, Granacher, Boullosa, Hackney, & Zouhal, 2020)). However, for the purpose of tactical analysis, GPS data is yet to be accurately transformed to the pitch-centered coordinate system, and the infrastructure of stadiums causes disturbance to the signal leading to inaccuracies in the data (Pons et al., 2019; Sathyamorthy, Shafii, Amin, Jusoh, & Ali, 2016). However, optical tracking systems have proven to be far more accurate and capable of tracking player positions with an error of less than 10 cm (Linke, Link, & Lames, 2020). Thus, the combination of positional and event data is used to apply machine learning techniques. Artificial intelligence (AI) relies on algorithms to predict new output values from historical data. These tools have accelerated the field of sports science and the operation of football clubs and federations (Mat Herold, Matthias Kempe, Pascal Bauer, & Tim Meyer, 2021; Linke, Link, & Lames, 2018; Rein & Memmert, 2016a). These tactical performance measures offer a more contextual-based, qualitative assessment of the dynamics of football with stronger ecological validity (Grant & Williams, 1999; Rein & Memmert, 2016a).

When discussing tactics, especially relative to different pitch areas, the conversation becomes about time and space. To better understand these spatial dynamics, researchers have created new variables such as length per width ratio, team centroid, team stretch index, the distance between teammate dyads, spatial exploration index, and player distance from the centre of team (Baptista et al., 2019; Coutinho et al., 2019; Folgado, Lemmink, Frencken, & Sampaio, 2014; Sampaio & Maçãs, 2012). Based on the theory that football can be broken into smaller parts, McGarry (2002) (McGarry, Anderson, Wallace, Hughes, & Franks, 2002) classified interactions as dyads (one vs. one) and collectives (many vs. many). As such, interpersonal coordination has been examined to understand how behavioral interaction occurs at both the micro (i.e., 1 vs. 1) and macro (i.e., 11 vs. 11) levels. In the context of a football match, network analysis defined “density” as the interconnectedness of nodes (players) in a network (team). For example, Grund et al. (2012) (Grund, 2012) found that higher density, demonstrated by greater passing rates, was correlated to an increased number of goals scored in 760 English Premier League matches in the 2006/07 and 2007/08 seasons.

One of football's greatest challenges is to anticipate teammates' and opponents' behaviour relative to the space and time dimensions throughout a match. Voronoi-diagrams based on algorithms have enabled researchers to detect team and individual movement patterns, correlations between players and team units, and how the team moves together when losing or gaining possession (Gudmundsson & Wolle, 2014). Using Voronoi diagrams, researchers could show how a region was considered dominant when one player could reach it before any other player (Lopes, Fonseca, Lese, & Baca, 2015). Key game events like shots on goal are accompanied by increased inter-team coupling variability, including strong coupling between team centroids (the average position of all the players on a team) (W. Frencken, Poel, Visscher, & Lemmink, 2012). Strong correlations were also found between the team’s centroid positioned in the lateral and longitudinal directions and concurrent match events. This mostly reflected the defensive team's collective behaviour to recover the ball. These objective measurements are helpful in the analysis of player distribution on the pitch and can be used to assess specific game situations.

Similar to team centroids, *betweenness* centralization refers to players' level of interaction during a match. A low level of *betweenness* centralization (close to 0) indicates that all players are equally important in maintaining ball possession. Conversely, a high *betweenness* centralization (close to 1) suggests that a single player is more important for a team to connect passes(F. M. Clemente, Martins, Kalamaras, Wong, & Mendes, 2015). Thus, a player with a high value of centralization plays a critical role in the passing networks. Centralized interaction patterns lead to fewer goals scored (Grund, 2012)and lower centralization was associated with successful teams(Pina, 2017). An example of this occurred in the 2010 World Cup, where champions Spain had the highest number of completed passes. Their low betweenness score showed that they were the most well-connected team with more players sufficiently offering support as passing options (Pena & Touchette, 2012). This coincides with other studies examining the relationship between spatial patterns of passes and performance, highlighting the role of central players who act as passing hubs (Gonçalves et al., 2017; Hirano & Tsumoto, 2005).

Each of the tactical metrics outlined above is influenced by the match context, which includes players' technical, physical, and tactical actions based on the coaches' instructions and their perception of the football environment. In other words, the passing action a player engages in could be determined by the movement and positioning of his teammate, and the tactical movement and positioning between teammates could be determined by the defensive organisation of the opponent. Therefore, to gain a deeper understanding of the use of data science in football, consider what, from a tactical perspective, practitioners value, what information data science can provide (i.e., off-ball behaviour), and how to implement the information to improve football performance are all needed. The combination of sports science and computer science expertise can also help to solve the problem of transferring scientific results into practice. In its early stages, a synergy between the domains of computer science and sports science already existed. Studies by Power et al. (2017) (Power, Ruiz, Wei, & Lucey, 2017), Spearman et al. (2017) (Spearman, 2018), Andrienko et al. (2017) (Andrienko et al., 2017) and Fernandez and Bornn (2018) (Fernandez & Bornn, 2018) involved expertise from data scientists with practical football knowledge. There are also examples of observational studies utilizing large datasets to create and validate new features of tactical performance (F. R. Goes, Kempe, Meerhoff, & Lemmink, 2018; Link, Lang, & Seidenschwarz, 2016; Rein, Raabe, Perl, & Memmert, 2016). Despite these initial steps, very little attention has been given to using data gathered via positional tracking to improve performance. This, along with identifying and researching existing gaps in the research, is a shortcoming that this thesis aims to address.

Chapter 2: Statement of Problems and Research Aims

Numerous research interests have been concerned with the relationship between data science and tactical play. However, most research was conducted outside the football community and lacked practicality and applicability. Instead of computer scientists continuing to create fancy metrics around passing behavior, the priority should be developing an understanding of how data science can be integrated into sports science. Furthermore, the creation of metrics and visualization tools can be a beneficial addition to measuring performance in understudied areas, such as off-ball. Finally, there needs to be an understanding of what practitioners value and utilize, including a systematic approach to integrating data science into football practice.

2.1 What is the status quo of data science and machine learning in football

Research is yet to clearly understand the contribution of data science and machine learning to tactical performance. Additionally, it remains unknown if there are factors associated with high-level football that may influence the usefulness of data-driven approaches. For instance, it is not yet known if the availability of information provided by machine learning positively influences performance, which may change depending on the specific metric, the practitioners involved, and the players' ability.

Furthermore, many studies in domains outside of football have focused on prediction and pattern recognition. Examining patterns from Spatio-temporal data primarily involves supervised detection of predefined patterns and the unsupervised exploration of new patterns. Machine learning algorithms can draw inferences from data, but football's chaotic nature poses challenges to researchers.

Aim 1: To review what studies exist using machine learning in football. This includes identifying limitations and areas of need for future work.

2.2 A Needs Analysis of Coaches and Analysts

Football is a complex sport that places unique demands on players' and teams' physical fitness, technical skill, and tactical recognition. Goals scored relative to the playing time of a ninety-minute match are rare and often occur due to chance. Thus, several attacking key performance indicators (KPIs) exist to help define success in more measurable ways. Technological advancements have led to new KPIs based on positional tracking data (e.g., Expected Possession Value) to go along with metrics gathered via notational analysis (e.g., Penalty Box Entries). However, there is no status quo about what coaches and analysts use and value in their practice.

Practitioners and scientists depend on what KPIs are needed and what KPIs are created or refined. Notably, on many occasions, the focus has been on creating newer and fancier KPIs when practitioners are unaware of existing ones or may not have access to the technology to implement them. Therefore, a survey of coaches and analysts across various countries and levels of play could prove helpful.

Aim 1: To assess what tactical key performance indicators coaches and analysts value and utilise

Aim 2: To identify how data science is currently being used and where it might fill a void in the status quo

2.3 How can data science be used to learn about off-ball behaviour in football?

The German Football Federation has a saying, "passing is the language of football". As such, several studies using data science in football have focused on passing behaviour as it is the most common tactical statistic. However, several components of the game determine the effectiveness of passes and influence the performance of a player and team. One of these factors is how players position themselves and move when they do not own the ball.

In Chapter 3, we identified a lack of research and tools to evaluate off-ball behavior. Developing a method to determine how individual players create space without the ball could help practitioners make more informed inferences about players' performance. Further, identifying how off-ball behaviour influences the Spatio-temporal aspects of the game adds a qualitative context to passing performance and attacking play.

A time-series analysis was used in the following study to evaluate the off-ball behaviour of attacking players in association football. The aim was to implement a defensive pressure model based on positional tracking data and combine it with notational analysis to make accurate inferences on two common off-ball behaviors: deep runs involving sprinting in a straight line and changes of direction.

Aim 1: To determine whether a model could be used to determine changes in defensive pressure over time. These changes include the amount of decrease in pressure, the length of time pressure decreased, and the rate at which pressure decreased.

Aim 2: Evaluate the frequency of off-ball actions and identify differences in pressure changes between playing positions.

2.4 Integrating Data Science into Practice to Improve Performance

Following on from the studies contained in Chapters 4 and 5 where we surveyed practitioners on the usage of KPIs and attempted to fill a gap in the research by examining off-ball behavior, respectively, the final step is to attempt to integrate data science to improve football performance. Traditional KPIs based on notational analysis inform practitioners about what occurred on the pitch, while data science approaches can provide information about how things occurred. However, no studies have attempted to utilise data science tools to improve football performance.

Aim 1: To apply two data-driven metrics, D-Def (defensive destabilization occurring from a pass) and the Number of Outplayed Opponents (how many opponents were eliminated from a pass in the longitudinal direction), to improve passing performance in professional players in the United States 2nd Division.

Chapter 3: Machine Learning in men’s Professional Football: Current Applications and Future Directions for Improving Attacking Play

Given the dynamic nature of football, various metrics may be useful to quickly and accurately quantify the behaviors and tactics used by players and teams throughout the 11v11 match-play. To date, no research has reviewed literature specifically relating to the use of technology to quantify tactical behaviors in professional football. Therefore, the literature review is needed to inform future research in this area.

This study has been accepted for publication following peer review. The content has been reformatted for this thesis. Full reference details for this study are:

Herold M, Goes F, Nopp S, Bauer P, Thompson C, Meyer T. Machine learning in men’s professional football: Current applications and future directions for improving attacking play. International Journal of Sports Science & Coaching. 2019;14(6):798-817. doi:10.1177/1747954119879350

3.1 Abstract

It is common practice amongst coaches and analysts to search for key performance indicators related to attacking play in football. Match analysis in professional football has predominately used notational analysis, a statistical summary of events based on video footage, to study the sport and prepare teams for competition. Recent increases in technology have facilitated the dynamic analysis of more complex process variables, giving practitioners the potential to evaluate a match considering contextual parameters quickly. One field of research, known as machine learning, is a form of artificial intelligence that uses algorithms to detect meaningful patterns based on positional data. Machine learning is a relatively new concept in football, and little is known about its usefulness in identifying performance metrics that determine match outcomes. Few studies and no reviews have focused on machine learning to improve tactical knowledge and performance, instead focusing on the models used or as a prediction method. Accordingly, this article critically appraises the application of machine learning in football-related to attacking play, discussing current challenges and future directions that may provide deeper insight to practitioners.

3.2 Introduction

The search for key performance indicators related to goal-scoring in elite association football is of great interest to researchers, coaches, and analysts. Researchers and practitioners have predominately utilised observational analysis to optimise their players' and teams' training process and game preparation.(Mike Hughes & Franks, 2005) Studies had shown successful football teams create more goal-scoring opportunities than the opposition(Winkler, 1996) by penetrating the defense(A. Tenga, Mortensholm, & O'Donoghue, 2017) and achieving greater entries into the penalty box (defined as "an event that took place either when the team in possession of the ball passed it into the opponent's penalty area, regardless of whether the pass was received by a teammate, or when a player in possession of the ball went into that area of the pitch") (J Lago-Ballesteros et al., 2012; Ruiz-Ruiz et al., 2013; A. Tenga et al., 2010b). These findings are valuable for identifying key game events; however, such time-consuming approaches give little or no consideration to team interaction, including rapidly changing contextual circumstances. Thus, the demand for more automated approaches to analyse tactical behaviour in men's professional football is increasing(C. Carling, Le Gall, McCall, Nedelec, & Dupont, 2015).

In the last decade, the ability to find key individual and team performance indicators have been greatly increased due to technological developments in (but not limited to) automatic tracking systems, video-based motion analysis, and Global Positioning System (Rossi et al.) units.(Christopher Carling et al., 2008) Wireless sensors have been widely used in training sessions, and FIFA has permitted its use to track player positions and physiological parameters during competitions.(Brud, 2017) Accounting for complex interactions occurring within a match, network analysis(Memmert & Perl, 2009) and Spatio-temporal metrics(F. M. Clemente, Couceiro, Martins, & Mendes, 2013; Johnson, 2006) have been employed for dynamic analysis and data simulation in sports.(R. Bartlett, Button, Robins, Dutt-Mazumder, & Gavin, 2012; Kelso, 1984; Laube, Imfeld, & Weibel, 2005; Prieto, Gómez, & Sampaio, 2015) Such information can help analysts, coaches, and players make crucial tactical decisions at the highest levels of elite football (M. Kempe, M. Vogelbein, & S. Nopp, 2016).

Aside from current approaches, machine learning in football is an emerging field of research used to reveal trends and distinguish between successful and less successful teams.(Mackenzie & Cushion, 2013; Sarmento et al., 2014) Machine learning entails utilising statistical and computational methods for classification, pattern recognition (similar to data mining), prediction (Wagenaar, Okafor, Frencken, & Wiering, 2017), and drawing inferences from datasets consisting of input data without labeled responses (Bialkowski et al., 2016). Machine learning is typically divided into two areas: supervised and unsupervised learning.

In supervised learning, one aims to optimise a model based on labeled training data to fit a given response. Case in point, the team tactic of penetrating passes can be learned by feeding the machine with examples of penetrating passes. Ultimately, supervised learning is aimed at satisfying the following equation:

$$y = f(x)$$

where y is a given response that is binary, multi-class, or continuous, X is the data comprised of features, and f is a function that machine learning attempts to optimise to approximate the equation. An example of supervised learning research in football is the work of Wei et al.(Wei, Sha, Lucey, Morgan, & Sridharan, 2013), who used a decision tree to map player movement to the response of different phases of the game (shots, corners, free kicks, etc.).

In unsupervised approaches, a model aims to uncover structures and patterns in unlabeled data. For example, for complex problems with an unknown desired response, unsupervised machine learning approaches have been used to measure inter-player coordination and team-team interaction, including the time preceding key game events such as shots on goal and compactness (Bialkowski, Lucey, et al., 2014b; Fernando, Wei, Fookes, Sridharan, & Lucey, 2015; Feuerhake, 2016; Memmert, Lemmink, & Sampaio, 2017; Xinyu, Long, Lucey, Morgan, & Sridharan, 2013). As an example of an unsupervised learning approach, Bialkowski et al.,(Bialkowski, Lucey, et al., 2014b) used tracking data to define a specific “role” within the team's formation for individual players at various game intervals. More specifically, they utilised minimum entropy data partitioning, which does not rely on a fundamental pre-determined model.

As illustrated by those examples, machine learning algorithms hold the potential to provide coaches and analysts with additional information to evaluate the game. By identifying specific patterns in large datasets, machine learning models can perform tasks such as automatically identifying team formations (Bialkowski, Lucey, Carr, Yue, & Matthews, 2014) or predicting how players move on offense and defense (Le, Carr, Yue, & Lucey, 2017). Further, due to the subjective perspectives of the coach or scout observing a game and rating the tactics, the data often lack objectivity and reliability(N James, Mellalieu, & Hollely, 2002). In this regard, machine learning may allow a more profound analysis of complex process variables, potentially offering more scientifically-backed, evidence-based information to coaches and analysts (Couceiro, Clemente, Martins, & Machado, 2014; Grehaigne et al., 1997; McLean, Salmon, Gorman, Read, & Solomon, 2017; Memmert & Perl, 2009).

As new possibilities arise with new data sources and approaches to analyse this data, there is a demand to further understand the advantages and limitations of applying machine learning methods to football (Bloomfield et al., 2005; L. Vilar, Araújo, Davids, & Button, 2012; Wallace & Norton, 2014). Tracking data contrasts with the traditional event data approach as the volume, variety, and precision provides detailed datasets to sports visualization researchers (Perin et al., 2018). Professional players nowadays are tracked during every training session and match by different systems, but the quality of data remains in question (Linke et al., 2018). Further, it is plausible that mounts of data without solid theory will not accurately inform decisions, and thus, these methods must be meticulously validated. Accordingly, a multi-disciplinary approach, including the collaboration of big data technologies with football research, may facilitate a comprehensive theoretical model and understanding of tactical performance. This review aims to critically appraise the literature related to machine learning in football and inspire the future application of these complex approaches in a more relevant manner.

This review consists of two sections: 1) a review of existing research on machine learning in football related to attacking play, outlining findings and limitations 2) emphasizing the practical application of machine learning, identifying challenges and suggesting avenues of future research to improve upon the features and practices associated with football performance.

3.3 Methods

A descriptive review of the available literature on match analysis in elite professional male football was conducted. Data were collected from the following computerized databases between 1996 and 2018: PubMed, Web of Science, MEDLINE, SPORTDiscus, Research gate, Elsevier, and ProQuest. Multiple searches were conducted. The search terms included: football, soccer, machine learning, match analysis, performance analysis, game analysis, notational analysis, dynamic analysis, and performance indicators.

The inclusion criteria for these articles were: (McHale & Relton) relevant data concerning technical and tactical evaluation, (McHale & Relton) participants, including professional adult male footballers (McHale & Relton) written in English. Studies were excluded if they: (McHale & Relton) included children or adolescents (under 18 years); (McHale & Relton) included females; (McHale & Relton) focused on set plays, small-sided games, or futsal.

The focus on professional male football was determined by several factors, including 1. greater relevance and a larger number of studies conducted with machine learning approaches using match data versus training data. This enables the comparison of different studies. 2. Behavioral differences between match play and training.(Olthof, Frencken, & Lemmink, 2019) 3. Studies using small-sided games have shown important physiological and tactical differences between 11 versus 11 football (Buchheit et al., 2014; Owen, Twist, & Ford, 2004). 4. There are differences in tactical behaviour between youth football and the elite (Almeida, Duarte, Volossovitch, & Ferreira, 2016).

To evaluate the included studies, we looked for several characteristics. The general machine learning approach (supervised vs. unsupervised), the specific machine learning approach (e.g., neuronal networks, k-nearest neighbor), the input data used (event vs. tracking data), and if the authors provided sufficient information to redo the analysis (see Table 1).

Table 1: Data Extraction Table (Machine Learning in Men's Professional Football)

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Hirano S and Tsumoto S[45]	Unsupervised (Clustering)	Multi-scale matching/induced dissimilarity matrix and rough clustering method	yes	Presented a method for grouping pass patterns such as side-attacks after complex pass transactions, and zig-zag pass transactions in soccer game records	Set the stage for future work to help coaches identify and execute passing patterns to increase goal-scoring.	64 games of the FIFA world cup 2002	event
Joseph A, Fenton NE and Neil M[81]	Supervised (Classification)	Several techniques were used: MC4, a decision tree learner; Naive Bayesian learner; Data-Driven Bayesian and a K-nearest neighbour learner.	yes	With an MC4 learner, identify attributes that have the largest effect on the game's outcome. The Bayesian network looked for correlations between the values of the attributes, including the result.	It can help analyse and identify important factors from past games	Matches played by Tottenham Hotspur (1995–1997)	event
Hucaljuk J and Rakipović A[80]	Supervised (Prediction)	Naïve Bayesian Network, KNN, ANN, Random Forests	yes	Based on the number of injuries, goals, team formation, and other factors training a supervised ML model to predict scores. ML model had 60% accuracy in predicting the score	The model can be improved and then can be used to predict the score and prioritise tactics accordingly	The group stage of the Champions League (96 matches)	event

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Lucey P, Bialkowski A, Carr P, et al.[61]	Supervised (Classification)	K-nearest neighbors	yes	Proposed a method to characterize the team behaviour for soccer by representing team behaviour via play segments, which are Spatio-temporal descriptions of ball movement over fixed windows of time. Using these representations, characterized team behaviour from entropy maps, which gives a measure of predictability of team behaviors across the field	Can be used to predict tactics using Spatio-temporal data	2010-2011 English Premier League soccer data	tracking
Chassy P[64]	Unsupervised (Clustering)	Principle component analysis (PCA) for clustering. Correlation to judge the efficacy of passing and compare it with possession	yes	Explored the idea that a football team can be formalised as a self-organising system. By applying the definition of self-organisation to football, the study concluded that team play constitutes the core of performance.	Coaches can use this information to improve passing behaviour	Data from 2013 European Champions League	event

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Xinyu W, Long S, Lucey P, et al.[24]	Supervised (Classification) and Unsupervised (Clustering)	K-means, PCA, Decision Trees	yes	Presented a method for large-scale analysis of team behaviour across large volumes of player and ball tracking data. Clustered plays of a team to describe their most likely motion patterns associated with an event (such as shots, corners, free-kicks). Proposed a two-layer hierarchical approach to automatically segment a match. Using a decision-tree formulation can accurately retrieve events or detect highlights	A useful method to improve the understanding of decision-making and identify patterns related to goal-scoring	Tracking data across nine complete matches from a top-tier European soccer league	tracking

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Bialkowski A, Lucey P, Carr P et al.[25]	Unsupervised (Clustering)	Expectation Maximization, k-means clustering, Minimum Entropy data partitioning	yes	Presented a role-based representation to represent player tracking data, which was found by minimizing the entropy of a set of player role distributions. Showed how this could be efficiently solved using an EM approach which simultaneously assigns players to roles throughout a match and discovers the team's overall role distributions	Can help perform individual player and team analysis, including large-scale team analysis over a full season	One season of ball tracking data from a professional soccer league (≈400,000,000 data points)	tracking
Lucey P, Bialkowski A, Monfort M, et al.[73]	Supervised (Prediction) Unsupervised (Clustering)	Logistic Regression and Conditional Random Field	yes	Found that not only is the game phase important (i.e., corner, free-kick, open-play, counter-attack etc.), the strategic features such as defender proximity, the interaction of surrounding players, speed of play, coupled with the shot location play an impact on determining the likelihood of a team scoring a goal	Can help coach know important factors leading to a goal	One season ball tracking data taken from a professional league (≈400,000,000 data points)	both

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Eggels RvEH and Pechenizkiy M[54]	Supervised (Prediction)	Logistic Regression, Decision Trees, Random Forests	yes	Proposed a method to determine the expected winner of a match by estimating the probability of scoring for the individual goal-scoring opportunities. The outcome of a match is then obtained by integrating these probabilities.	Can pre-strategize according to predicted results obtained using the proposed model	Event Data tracked by ORTEC. Data about the quality of players was extracted from the web. Spatiotemporal data from seven different leagues over three seasons	both, but only classified with event data due to accuracy issues with Ortec
Fernando T, Wei X, Fookes C, et al[26].	Unsupervised (Clustering)	k-means	yes	Presented a method that can be used to compare the scoring methods of teams in soccer using fine-grained player tracking and ball-event data	Help compare goal scoring style of teams	One season of tracking data from Prozone consisting of 20 teams	tracking
Horton M, Gudmundsson J, Chawla S, et al.[57]	Supervised (Classification)	Multinomial Logistic Regression.	yes	Presented a motion model that calculates regions such as "passable regions" for every pass that can learn a classifier to rate the quality of passes made during a football match with an accuracy of up to 85.8%. Evaluated passes according to difficulty or decision quality	Help use quality of passes to train players on improving their passing behaviour	4 Home Games of Arsenal Football Club	both

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Montoliu R, Martín-Félez R, Torres-Sospedra J, et al.[46]	Supervised (Classification)	Bag of Words, k-Nearest Neighbor, the Support Vector Machine and the Random Forest	yes	Proposed a new method based on using local motion features and a Bag-of-Words strategy to characterize short Football video clips. The approach can correctly distinguish between actions related to Ball Possession, Quick Attack, and Set-Piece plays. The proposed bag-of-Word feature vector appropriately captures the behaviour of players. The proposed method is useful to analyse the most common movements of a team when playing a match. The Random Forest classifier obtains the best classification	It can be used to predict the opponent's activity and prepare for it more quickly. Identify the opponent team's strengths and weaknesses before the match, obtain the opponent's main tactics during a match, observe his/her team's performance during a match, and evaluate the players as a whole or individually immediately after the match, among other possible applications	A private dataset of Football videos of 4 games	Event
Ruiz H, Lisboa P, Neilson P, et al.[53]	Supervised (Prediction)	Multilayer Perceptron (algorithm for supervised learning of binary classifiers)	yes	The model can predict shot expectancy accurately and can be used to strategise for an advantage	Modelling the expected goal value of shots gives an additional level of detail to the analysis of offensive and defensive performance in football	10318 shots taken during 2013/14 English Premier League, extracted from Prozone Matchviewer event data	Event

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Tax N and Joustra Y[82]	Supervised (Prediction)	Principle component analysis, Naïve Bayesian, Multilayer Perceptron	yes	The model can predict the result of a match using relevant input up to a high accuracy	It can be used to determine areas where a team needs to improve on and/ or plan strategy to combat the expected result	A public data-based match prediction system for the Dutch Eredivisie	event
Bialkowski A, Lucey P, Carr P, et. al. [22]	Unsupervised (Clustering)	Expectation Maximization, k-means clustering, Minimum Entropy data partitioning	yes	Could identify team structure or “formation,” which served as a strong descriptor for identifying a team’s style.	Can be useful for strategic planning, evaluation, and tactical adjustments	Twenty teams played home and away. Thirty-eight matches for each team or 380 matches overall. Six of these matches were omitted due to missing data.	tracking
Brooks J, Kerr M and Guttag J[48]	Supervised (Classification & Prediction)	K-Nearest Neighbors	yes	Using heatmaps and KNN, ranked offensive players and identified team patterns using passing data	Can help improve passing behaviour	2012-2013 La Liga season. Dataset provided by Opta Sports.	Event

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Feuerhake U[27]	Supervised (Classification) and Unsupervised (Clustering)	k-means, Apriori, Levenstein distances, DBSCAN, Euclidean movement space	yes	Used distances, clustering, and classification to analyse the sequence of movements (pattern recognition) in a soccer game	It needs more research, but being able to predict the trajectories of players can potentially help coaches devise tactical plans and for player selection that favours different playing styles	Three datasets with different characteristics. The first two datasets contain movement information of players during football matches, and the third contains car trajectories and thus is from a completely different context	tracking
Knauf K, Memmert D and Brefeld U[67]	Unsupervised (Clustering)	Clustering tasks and k -medoids. Temporal kernels were Gaussian kernels combined with three different spatial kernels	yes	Presented Spatio-temporal convolution kernels for multi-object scenarios	Clusters can help coaches identify how teams behave in the attack. i.e., teams preferring many short moves that involve multiple players versus teams utilising long moves with more linear actions and fewer ball contacts	Ten soccer games of the German Bundesliga from the 2011/2012 seasons	tracking

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Szczepański Ł and McHale I[60]	Supervised (Classification & Prediction)	Additive Mixed Modeling	yes	Presented a method that can be used to evaluate the passing skill of footballers controlling for the difficulty of their attempts. Combined proxies for various factors influencing the probability that a pass is successful in a statistical model and evaluate the inherent player skill in this context.	Coaches can use it to improve passing for players	2006–2007 season of the English Premier League provided by Opta	event
Chawla S, Estephan J, Gudmundsson J, et al.[59]	Supervised (Classification)	Multinomial Logistic Regression	yes	Present a model that can teach a classifier to rate the quality of passes made during a football match with an accuracy of up to 85.8%. Furthermore, a rating of the quality of each of the passes made in the four matches was made by two human observers	Help use quality of passes to train players on improving their passes	Four home matches played by Arsenal Football Club (2007/08)	both
Le HM, Carr P, Yue Y, et al.[30]	Supervised (Prediction)	LSTM Neural Networks	yes	Generated the defensive motion pattern of the “league average” team, resulting in a similar expected goal value (69.1% for Swansea and 71.8% for the “league average” ghosts	Further research can help build automated strategies against specific opponents	100 games of player tracking and event data from a professional soccer league	tracking

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Memmert D, Lemmink KA and Sampaio J[28]	Supervised (Classification) and Unsupervised (Clustering)	Neural Networks	yes	Demonstrated different kinds of computer science approaches to obtain and analyse new parameters such as inter-player coordination, inter-team coordination before critical events, and team-team interaction and compactness coefficients	Potentially help coaches modify their training methods (e.g., focusing on recent trends in game philosophy and tactics) according to their needs and improve the tactical behaviour of their players. It can be an important step toward the objectification of tactical performance components in team sports	A single set of position data from an 11 versus 11 match (Bayern Munich against FC Barcelona)	Event
Pappalardo L and Cintia P[47]	Supervised (Classification & Prediction)	Logistic Regression	yes	A team's position in a competition's final ranking is significantly related to its typical performance, as described by a set of technical features extracted from the soccer data. Victory and defeats can be explained by the team's performance during a game, but it is difficult to detect draws	It helps coaches prioritise objectives and predict success based on performance features correlated to success	More than 6,000 games and 10 million events in six European leagues.	Event

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Power P, Ruiz H, Wei X, et al.[75]	Supervised (Classification) Unsupervised (Clustering)	Logistic Regression and k-means clustering	yes	Presented an objective method of estimating the risk and reward of all passes using a supervised learning approach	It can be used to coach and choose players according to the opposition in terms of pass risk and reward	English Premier League games between 2014/15-2015/16 seasons totaling 726 matches.	Both
Rathke A[52]	Supervised (Prediction)	Logistic Regression	yes	Demonstrated the value and reliability that xG has within professional football. The variables of distance and angle together were seen to have a major impact on calculating xG rather than distance as a variable alone.	No direct practical application; however, it could be incorporated into training and as a teaching tool on both offense (how attacking players should strike certain shots) and defense (optimise positioning to defend dangerous shots)	Shots from the Premier League and Bundesliga games (380 & 306) from the 2012-2013 season	event
Ruiz H, Lisboa P, Neilson P, et al.[53]	Supervised (Prediction)	Multilayer Perceptron	yes	The model can predict shot expectancy accurately and can be used to strategise	Modelling the expected goal value of shots gives an additional level of detail to the analysis of offensive and defensive performance in football	10318 shots taken during 2013/14 English Premier League, extracted from Prozone Matchviewer event data	event

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Barron D, Ball G, Robins M, et al.[51]	Supervised (Classification & Prediction)	Multi-layer Artificial Neural Network	yes	Using match and player data and an artificial neural network, the model learns which player can be helpful to the team by predicting his career trajectory using quantifiable features.	Possibly useful for player recruitment	Performance data from 966 outfield players90-minute performances in the English Football League.	event
Goes FR, Kempe M, Meerhoff LA, et al.[62]	Supervised (Prediction) Unsupervised (Clustering)	Multiple Linear Regression, PCA	yes	The presented approach is the first quantitative model to measure pass effectiveness based on tracking data that are not linked directly to goal-scoring opportunities	Help coaches train their players to increase the efficacy of passes	Eighteen competitive professional soccer matches of 1 team against 13 different teams during the 2017–2018 Dutch premier league (Eredivisie).	Tracking
Hobbs J, Power P, Sha L, et al.[77]	Unsupervised (Clustering)	Spatiotemporal Trajectory Clustering	yes	Could objectively and automatically identify counterattacks and counter-pressing without requiring unreliable human annotations	Knowledge about the types of plays a team runs immediately after regaining the ball has been used for tactical planning and game adjustment	Counter-attack data both for and against each team during the 2016-2017 English Premier League	tracking

Study	ML Approach	Used ML Algorithms	Reproducible details reported	Study Synopsis	Transfer to Practice	Data	Tracking vs. Event Data
Spearman W[76]	Supervised (Classification)	Logistic regression and Bayesian approach.	yes	Presented a new approach to using this tracking data to quantify off-ball scoring opportunity (OBSO). This metric can be used as a leading indicator of future player scoring, and there are many possible applications for the opportunity model	It can be used to improve players' off-ball movement and improve passing decisions. Use as a scouting tool to identify players who are making good movements off the ball but are not being rewarded with passes	Fifty-eight matches were played between teams from a 14-team professional soccer league during the 2017-2018 season.	Both

3.4 Machine Learning in Football

This section will review the existing research on machine learning in football-related to attacking play, outlining findings and limitations. This section is split into two: studies using event data and studies using tracking data.

3.4.1 Machine Learning Models in Football Using Event Data

Event data is the standard source to quantify and evaluate individual and team performance in recent decades (Carlos Lago-Peñas & Dellal, 2010; Sarmento et al., 2014). Event data consists of outcome measures such as frequencies, proportions, and other accumulated performance indicators of events happening throughout a match (Carlos Lago-Peñas & Dellal, 2010). In general, those studies were interested in identifying tactical patterns in a game using unsupervised machine learning approaches or predicting individual or team success using supervised approaches.

To derive tactical patterns from match data, Hirano & Tsumoto(Hirano & Tsumoto, 2005) created a multi-scale matching and rough clustering method based on temporal event data consisting of 168 time-series sequences from 64 games of the 2002 FIFA World Cup. Pass patterns such as side-attacks and zig-zag transactions leading to a goal could be automatically clustered. In another implementation of a pattern recognition approach, Montoliu, Martín-Félez, Torres-Sospedra, et al.(Montoliu, Martín-Félez, Torres-Sospedra, & Martínez-Usó, 2015) formulated a Bag-of-Words-based method to analyse the most common movements in a dataset of two regular Spanish La Liga matches played by four professional teams. Among other possible uses, common team activities such as ball possession, quick attacks, and set-piece plays could be recognized to identify and evaluate one's team, and the opponent team's strengths and weaknesses before, during, and after a match. Although the results of those studies were promising, the quality of their models should be questioned due to the relative low number of data points. In addition, they did not include test sets of data not used to build their models and validate them.

A recent study involving a much larger dataset, including 6,396 games and 10 million events from the 2013/2014, 2014/2015 and 2015/2016 seasons of the Premier League, Serie A, La Liga, Bundesliga, Dutch Eredivisie, Ligue 1, used machine learning to quantify the relation between performance (passes, crosses, shots, tackles, dribbles, clearances, goalkeeping actions, fouls, intercepts, aerial duels, goals scored and goals conceded) and success based on goal difference (Pappalardo & Cintia, 2017). The logistical regression and classification model could predict simulated team rankings close to the actual rankings. The discriminatory features between the top and bottom teams included producing more passes and shots than the opponent and committing fewer fouls, tackles, and goalkeeping actions.

Although the events extracted from the match appear like traditional notational analysis, a team's playing quality, including pass precision and spatial and temporal dominance, including average team position, speed, and accelerations, could also be measured. However, there was some observed divergence due to the erratic nature of football, such as psychological factors and contextual factors either not captured by soccer logs or not measurable by existing technologies. It was concluded that combining their data logs with player tracking data and mathematical models could better describe the Spatio-temporal trajectories of players during a match. In addition, reproducing game patterns between two teams would more accurately characterise the relation between technical performance and success.

In addition, to pass quality and variability, the location of passes is also a determinant of a successful offense. Providing context related to playing in critical pitch zones, Brooks, Kerr, & Guttag(Brooks, Kerr, & Guttag, 2016) used a k-nearest neighbor approach to qualitatively assess the effect of passes traveling into and out of Zone 14, the zone located in the middle of the pitch immediately outside the opposing penalty area (see Figure 1). Based on all passes from the 2012–2013 Spanish La Liga season, possession in Zone 14 often correlates to shooting opportunities. This supports previous studies using notational analysis, where Zone 14 was correlated with assists by making forward passes into the penalty areas (Grant & Williams, 1999; Horn, Williams, & Ensum, 2002). However, one limitation of using pitch zones is that achieving possession in a specific zone does not guarantee or provide information about whether a team penetrates the opponent's defense. As an illustration, a team with possession in Zone 14 can still face opposition with 11 players behind the ball, such as a rebound after a set play, or against a team that tactically emphasises a defensive structure. Moreover, long completed passes showed a negative relationship with shots taken, suggesting teams should consider how the ball arrives at Zone 14 (Brooks et al., 2016).

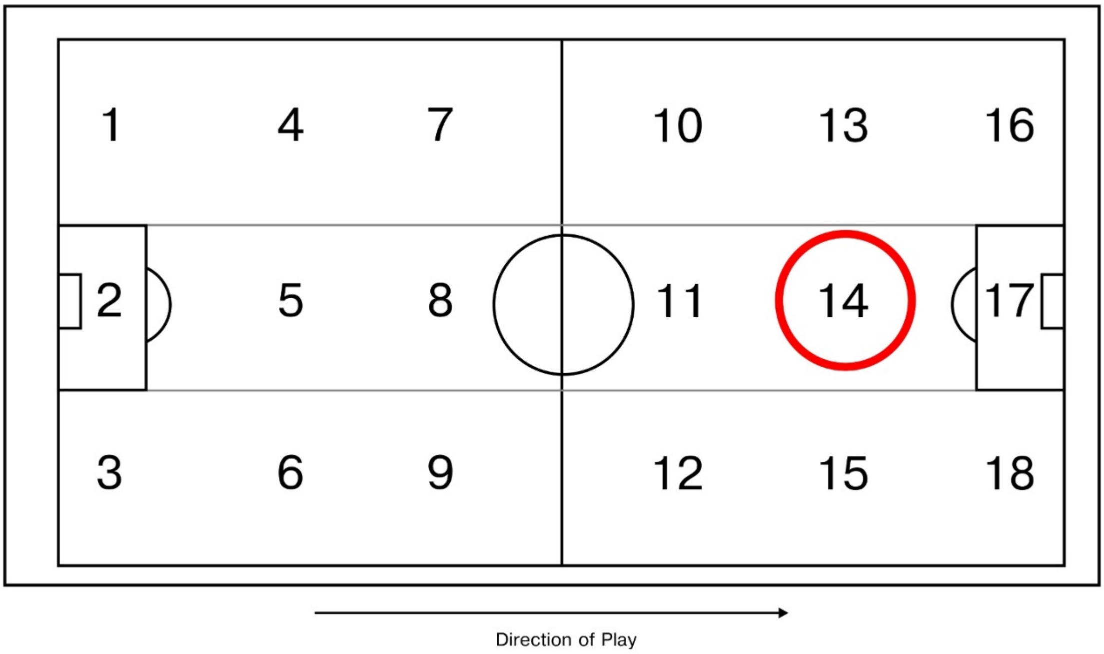

Figure 1: Zone 14: By dividing the field into a six-by-three grid, there are 18 zones on the pitch. Zone 14 is the zone located in the middle of the pitch immediately outside the penalty area

In a study demonstrating the potential for machine learning to be used in the scouting and recruitment process in professional football, technical performance data was collected from 966 outfield players in the English Football League Championship during the 2008/09 and 2009/10 seasons (Barron, Ball, Robins, & Sunderland, 2018). Key performance indicators that influence players' league status and accurately predict their future success in football were identified using quantifiable features, circumventing the subjective process and bias using traditional notational observation. For example, players most likely to end up in the English Premier League averaged the fewest unsuccessful first-time passes, had a higher mean number of possessions, and averaged more passes to teammates in the penalty area. The authors stated that future work assessing players should account for positional differences and pass accuracy over varying distances and directions in specific pitch areas.

In recent years, an expected goal value (xG) model has been developed to evaluate the offensive performance of players and teams. The xG model assigns a value between 0-1 (with 1 being the maximum and representing a certain goal) to every attempt based on the quantity and quality (i.e., assist type, shot angle and distance from goal, whether it was a headed shot, etc.) of shots taken. While a variety of these models have proven valuable in predicting shooting outcomes and scouting for players with high conversion rates, they either did not acknowledge (Rathke, 2017; Ruiz, Lisboa, Neilson, & Gregson, 2015) or capture (Eggels & Pechenizkiy, 2016) opponent positioning and, thus, failed to provide context that coaches and analysts can apply to the match. Studies conducted to predict individual, or team success used larger samples to build their model. However, they mostly used simple regression models to build classification or prediction models.

3.4.2 Machine Learning Models Using Tracking Data

In the second part of the review, we present studies using tracking data to build their machine learning models. One of–the advantages of tracking data is that it allows analysts to make quantitative comparisons between two teams, different groups of players, or among different individual players (Z. Yue, Broich, Seifriz, & Mester, 2008). Therefore, newer studies using machine learning approaches tend to use richer input data. In general, machine learning approaches in this section can be split into four thematic sections. The first includes studies that try to find patterns of pass sequences or evaluate passes of individual players, while the second looks at the same characteristics on a team level. The third line of research investigated the use of time and space to create goals and goal-scoring opportunities. The last section concerns defending or regaining the ball (in this case, the concept of pressing).

3.4.2.1 Pass Pattern Recognition and Classification

Advanced analysis of offensive tactics has mostly included the study of movement patterns and passing behavior. For instance, using simulation data, Gudmundsson & Wolle (Gudmundsson & Wolle, 2014) created a 2D model based on Frechet distance and the average Euclidean distances between trajectory paths to cluster sequences of passes between distinct players. After inputting 23 trajectories representing the ball's movement and 22 players on the pitch, the model automatically outputs a description of every possible pass. They could then assess a player's ability to execute a pass, become available for a pass, and receive a pass. They could also measure a player's perception and decision-making ability based on all passes made and missed.

However, the authors concluded that the incorporation of a classification scheme (including examples of “good” and “bad” passes determined by expert football analysts) would be necessary before the tool could be used by coaches and analysts on a practical level. Implementing such a classification scheme, Horton et al. (2015)(Horton, Gudmundsson, Chawla, & Estephan, 2015) added to Gudmundsson and Wolle’s (Gudmundsson & Wolle, 2014) motion models by incorporating a multinomial logistic regression model (supervised learning). Given input data from four home matches played by Arsenal football club consisting of 2,932 observations, the input features included: location of players, player trajectories, strategic positioning of a team based on dominant regions(Taki & Hasegawa, 2000), and physiological attributes using a motion model to determine how quickly a player can reach a given point. In addition, Cohen's kappa coefficient was calculated as a heuristic to evaluate and validate the use of a machine learning classifier for the inter-rater agreement between the two observers.

The authors yielded a score of 0.393, concluding that the experts were in moderate agreement. From this, the model could predict the quality of a pass of Good, Ok, and Bad with an accuracy of 85.6%. Due to a limited number of observations, the labels were then condensed from a 6-class problem to a 3-class problem. Although accuracy was high, precision and recall were relatively low, stating that false negatives and false positives were high. In other words, passes classified as good were indeed “Bad” or “Ok” and vice-versa. The greatest limitations of this paper are the absence of data and the use of only two observers, which is not enough to reach a consensus. Despite these limitations, the methodology set the stage for future work, including the design of improved predictor variables.

Further expanding on the earlier work exploring pass classification, a supervised machine learning model was developed by Chawla, Estephan, Gudmundsson, et al. (Chawla, Estephan, Gudmundsson, & Horton, 2017) to automatically classify the quality of all passes on the field. Passes were labeled as “Good,” “OK,” or “Bad”, with an accuracy level of 90.2% between the classifier ratings and the ratings made by a human observer. Although the accuracy was high, the subjective rankings were limited because they did not give quantitative measurements of pass effectiveness or information about ball velocity, ball trajectory, and what direction players faced during each pass (a common issue with tracking data). Despite challenges, the technological progress enabling analysts to classify passes can be a scouting tool. By applying Spatio-temporal metrics to player trajectories, Feuerhake (Feuerhake, 2016) could recognize and predict individual and group movement patterns, including differences between playing positions. For example, the wing players use straight runs fixed along the sideline compared to the central midfielder displaying more freedom and significantly more turns.

However, real-time information about why a player might have changed their behaviour could not be provided due to computational complexities. Another study focused on creating an individual evaluation tool for player recruitment and evaluated the passing ability of individual players by controlling for the difficulty of their attempts based on the probability of completion (Szczepański & Mchale, 2016). Contextual factors such as the player's skill and the conditions of the player passing the ball could not be considered. Only the distance between the passer and receiver could be derived directly from the model. Thus, comparing players performing similar types of passes in similar circumstances was most useful. The authors suggested that future work should account for different playing positions and defensive pressure, and rather than their difficulty, passes should be evaluated by their value for the team.

To summarise this section, the authors used more complex machine learning approaches to cluster (unsupervised) or classified (supervised) passes. As a result, a higher degree of data variety could be observed compared to the event data studies as authors tried to enrich their models. In addition, the methodology used in those studies was solid, as they validated their models with a test set that was not part of the training data.

3.4.2.2 Team Passing Behaviour

In a first attempt to utilise artificial intelligence to provide process-oriented tactical insight in a football match, the validity of an unpredictable passing strategy was investigated by tracing *play segments* defined as Spatio-temporal descriptions of ball movement (where the ball started and ended) over fixed windows of time. Measuring ball trajectories in 380 games from the English Premier League showed a high level of entropy, a measure of predictability for team behavior, which was an attribute of the top 5 ranked teams. This was the case, especially around the penalty area, where more defensive players were trying to protect their goal (Lucey, Bialkowski, Carr, Foote, & Matthews, 2012). The authors then attempted to show how discriminative their entropy map approach was by identifying the home versus away team based on classification of playing style using a k-Nearest Neighbor approach. Combining their entropy map approach with twenty-three match statistics currently used in the analysis (e.g., passes, shots, tackles, fouls, aerials, possession, time in-play etc.), they reached 47% classification accuracy. Coaches and analysts can use this information to measure their team's entropy levels and opponents. However, knowledge about what types of off-ball movements encouraged the greater variety of passing and how specific passing sequences lead to goal-scoring could not be identified.

Earlier work using notational analysis provided evidence that direct counter-attacking tactics effective against imbalanced defenses (defined "as only without a second defender within 5 m estimated distance from the first defender") are not necessarily effective against balanced ones (A. Tenga et al., 2010b). For that reason, evaluating the quality of a pass should be considered the effect a pass has on the opposition. For the interactive dynamics of both teams to determine the effects of passing behavior, Goes et al. (F. R. Goes et al., 2018) considered previous research on team centroid, spread, and surface (W. Frencken, Lemmink, Delleman, & Visscher, 2011) in evaluating defensive organisation. Goes et al. (F. R. Goes et al., 2018) calculated the D-Def (defensive disruptiveness) score as an index representing the defensive organisation's change resulting from a pass. Based on the line formations and starting formations (substitutions accounted for) of teams provided by coaches before the match, D-def was calculated based on the displacement of the average X and Y positions (or centroids) for the full team. In addition, the defensive, midfield, and attacking lines between the moment a pass was given (t0) and 3 seconds later (t0+3).

The authors discovered that greater amounts of individual movement (I-Mov) occurring after a pass result in a disruption of the defensive organisation (D-Def). Moreover, they could distinguish top, average, and low performance passes, and determine which players are more effective passers using a one-way ANOVA comparing the I-Mov, D-Def, pass length, pass angle, and pass velocity in the top 10%, average of 80%, and bottom 10% passes ranked on D-Def score. Consistent with the findings of Chassy (Chassy, 2013), the speed and precision of passes are predictors of success, causing greater D-Def scores. Although passes in a slightly more forward direction produced the best D-Def scores, the passing angle was not a determining factor for the effectiveness of passes. This was the first model that did not favor passes in the forward direction, demonstrating the value of backward and sideways passes in the overall attacking process.

Still, previous studies have shown that teams with increased space control in the attacking third have a greater chance of winning (Rein, Raabe, & Memmert, 2017), with the scoring probability increasing as the distance from the goal decreases and centrality increases (Link et al., 2016). Therefore, Goes et al. (F. R. Goes et al., 2018) suggested that to rate the actual effectiveness of a pass, future work should incorporate pitch values to measure space creation and investigate the relationship between D-Def and game outcome (goals). Furthermore, by only including successful passes, the authors could not measure decision-making or determine whether a certain player was a good passer overall.

In related work analysing both player trajectories and passing behaviour for two different teams in the Bundesliga 2011/2012 season, Knauf, Memmert, & Brefeld (Knauf, Memmert, & Brefeld, 2016) used Spatio-temporal convolution kernels to extract strategies used during the buildup phase of an attack and scoring opportunities. The authors could identify the difference between teams utilising rehearsed methods consisting of shorter passes amongst several players compared to more chaotic approaches characterised by long, straight passes. The studies presented in this section show much potential for practical applications. The main weakness of most of the presented studies is that their data sample is on the edge of being big enough to conduct their used methods.

3.4.2.3 Team Behaviour Related to Time, Space, and Goal-Scoring

Studies using a multiple regression model(Oberstone, 2009) and comparative analysis(Castellano et al., 2012) have reported that successful teams create more shots and shots on target. Other studies using notational analysis suggest that rather than the total number of shots, shot effectiveness best discriminated between successful and unsuccessful performance (Carlos Lago-Peñas & Dellal, 2010; Szwarc, 2004a). Machine learning methods based on tracking data have also been used to evaluate offensive tactics related to space and time management.(Grunz, Memmert, & Perl, 2012; Perl, Grunz, & Memmert, 2013). Applying a machine learning approach to gain insight into the process behind creating more effective scoring chances, Lucey, Bialkowski, Monfort, et al. (Lucey, Bialkowski, Monfort, Carr, & Matthews, 2014) used the spatiotemporal patterns of the ten-second window before a shooting attempt to determine that expected goals depend on several factors. These include the interaction of surrounding players, speed of play, and support of the observational analysis by Schulze et al.,(Schulze et al., 2018) shot location and defender proximity to the shooter.

Compared to statistics such as shots and shots on goal that do not provide information on the quality of the shooting attempt, their xG model could provide a better approximation about whether a team was "dominant", with many quality (high xG value) chances, or "lucky", with significantly fewer quality chances but still won the match. However, isolated plays such as their finding that "a play which has the left-winger controlling down the left uncontested and then slotting the ball between the back four to a player in the six-yard box results in a chance of 70.59%" (p.7) (Lucey et al., 2014) does not explain the origins of that scenario, nor how the probabilities may change depending on specific players being utilised against various opponents.

In another study involving the concept of a ten-second window before a shot, Power, Wei, Ruiz, et al. (Power et al., 2017) used tracking data to evaluate passes based on risk, the likelihood of executing a pass in each situation, and reward, the likelihood of a pass creating a chance. They defined a Dangerous Pass (DP) as an attempted pass with a greater than 6% chance of leading to a shot in the next 10 seconds. It was discovered that the passes with the highest reward (DP) occurred around the edge of the penalty area, and these passes also have the highest risk. The ability of a team to play high reward passes that lead to scoring chances also depends on the function of players not in possession of the ball.

Similar to calculating expected goals based on instantaneous game state, Spearman et al. (Spearman, 2018) created opportunity maps based on Spatio-temporal tracking data to measure "off-ball scoring opportunity" (OBSO), the probability that a player currently not in possession of the ball will score. This study also measured individual finishing ability, team attacking trends, and team decision-making within and around the penalty area by comparing OBSO to actual goals scored. The model suggested-that certain players get into dangerous positions but are not always rewarded with a pass, and some players have distinct pitch zones where they are more dangerous. This information is valuable to coaches and analysts as a tool to scout for prospective players, prepare for specific opponents, evaluate offensive movement and decision-making, and answers questions about how some players´ off-ball movement gives them seemingly greater "instinctive" qualities. This model, however, fails to assess how different types of defensive pressure and player speed influence the ability to successfully deliver a pass to a teammate. Furthermore, this method of measuring OBSO does not include information about how individual skill and awareness determine conversion rates and why some players and teams have lower conversion rates than others.

3.4.2.4 Defense and Pressing Tactics Related to Attacking Play

In a continuous, interactive sport like football, there are frequent turnovers of the ball from one team to the other. Attacking sequences occurring quickly after recovering the ball facilitate space exploitation in the defense. Due to the inherent imbalance of a team transitioning from offence to defense, counter-attacks generated a greater number of high-quality shots, and top teams were effective at utilising and stopping counter-attacks (Hobbs, Power, Sha, Ruiz, & Lucey, 2018). Hobbs et al. (Hobbs et al., 2018) implemented machine learning to automatically identify the precise time-stamp of counter-attacks and come up with a metric known as *"offensive threat",* the likelihood of a shot being taken in the next 10 seconds. The authors also identified the types of plays a team runs immediately after regaining the ball. The challenge remains to identify how parameters such as the direction and the total number of passes, time taken, and distance covered correspond to a counter-attack's success. Nevertheless, machine learning-based studies could exceed the capabilities of notational analyses (D., Garganta, Guimarães, Machado, & Anguera, 2014) and provide a method for evaluating team tactical behaviour and understanding that of their opponents.

Using advanced machine learning methodologies called "deep imitation learning" (a subfield of machine learning that can learn and make intelligent decisions on its own), researchers compared fine-grain movement patterns from a season's worth of tracking data from the English Premier League (Le et al., 2017). Although it has only been presented at a rather commercially oriented conference, and some critical distance should be exercised, their ghosting method could access the location, velocity, and acceleration of every player at the frame level to visualize the defensive movement patterns of a league-average team. By fine-tuning the model, they could also identify how a specific team would have responded to an attacking situation. For example, if the opponent produces a shot on goal, the hypothetical ghosting player would have more proactively closed the player's passing lane, preventing the shot. The capacity to estimate how a team could have responded to an offensive situation enables coaches and analysts to measure the effectiveness of defensive positioning. Moreover, a broader understanding of defensive tactics and team trends facilitates the scouting process and the development superior attacking strategies.

3.5 Current challenges and future directions of machine learning in football

3.5.1 Current challenges of machine learning in football

The latest advances in technology have the potential to add novelty and speed to exploring contextual variables related to football. The automatic, quantitative analysis that machine learning offers is beyond the scope of observational analysis, as supervised classifying models can produce the same and richer observational data (Chawla et al., 2017). We differentiated between two types of input data: event data and tracking data. The main findings from event data include recognizing team patterns and characteristics and identifying key performance indicators as predictors of success. The main findings from tracking data were more process-oriented, such as the determinants of effective passes and the scoring probabilities of players not possessing the ball or after quick regains. Studies used classification/clustering to model decisions experts normally make and predict goals, game outcomes, and league success (see Table 2).

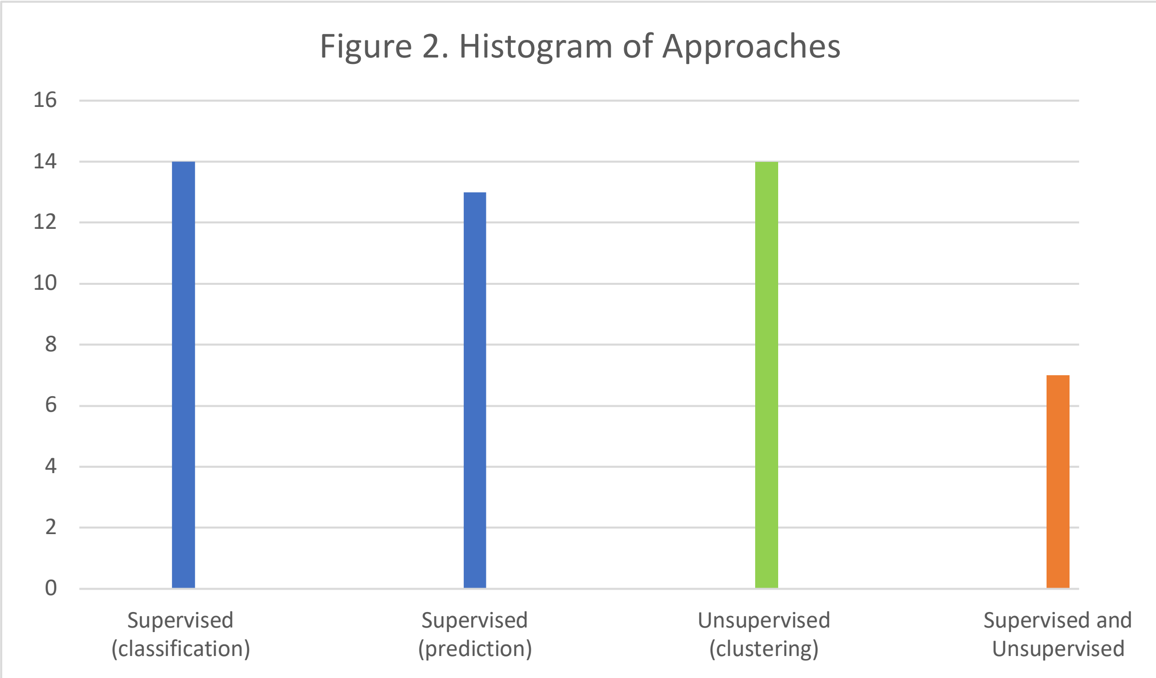

Figure 2: Frequency distribution of studies using supervised learning, unsupervised learning, and both. Within supervised learning, prediction (continuous y variable) Predictions (continuous y variable) within supervised learning versus classification (categoric)

Despite the advantages of tracking data, scenarios involving quick, unpredictable movements, including frequent occlusions between players, provide challenges to practitioners regarding the accuracy of the information provided compared to what is occurring on the pitch (Linke et al., 2018). Future projects should be aimed at diminishing these inherent errors (Linke et al., 2018), and it is recommended that practitioners use caution when comparing results between different tracking systems. Nonetheless, player tracking data is being used more and more frequently by teams to turn raw data into useful information.

Most studies using machine learning are performed by computer scientists as they use more complex approaches. However, the downside of using those complex models is that they result in a "black box" where a result (model) is obtained (especially using neuronal networks), but determining what the important factors are is not always possible. For instance, you can have a passing model that does a good job quantifying passes, but it does not tell if pass length, velocity, position etc. makes it a good pass. Thus, it is hard to provide feedback to coaches and practitioners who favor straightforward analyses that provide a quick "snapshot" of the team's performance (C. Carling et al., 2015). Performance analysis research, including substantial and complex statistics and mathematical equations, are not priorities for coaches, nor have they been successfully integrated into coaching (McLean et al., 2017). As such, the majority of machine learning analysts' work has been done by computer science research groups with little involvement from sports scientists, match analysts, or coaches (Rein & Memmert, 2016a).

Additionally, many studies have aimed at match prediction, which offers little in terms of how conclusions are drawn outside of which team is more likely to outscore their opponent (Fernando et al., 2015; Hucaljuk & Rakipović, 2011; Joseph, Fenton, & Neil, 2006; Tax & Joustra, 2015). Due to the lack of interaction between practice and computer science, the outcomes seldom transfer into practice, leaving considerable room to improve upon applying knowledge gained by the data to knowledge that can be applied to the actual game. Therefore, it is suggested that machine learning analysts/computer scientists, sports scientists, and football coaches/analysts combine to obtain more accurate information concerning individual and collective performance that may influence the outcome of football matches.

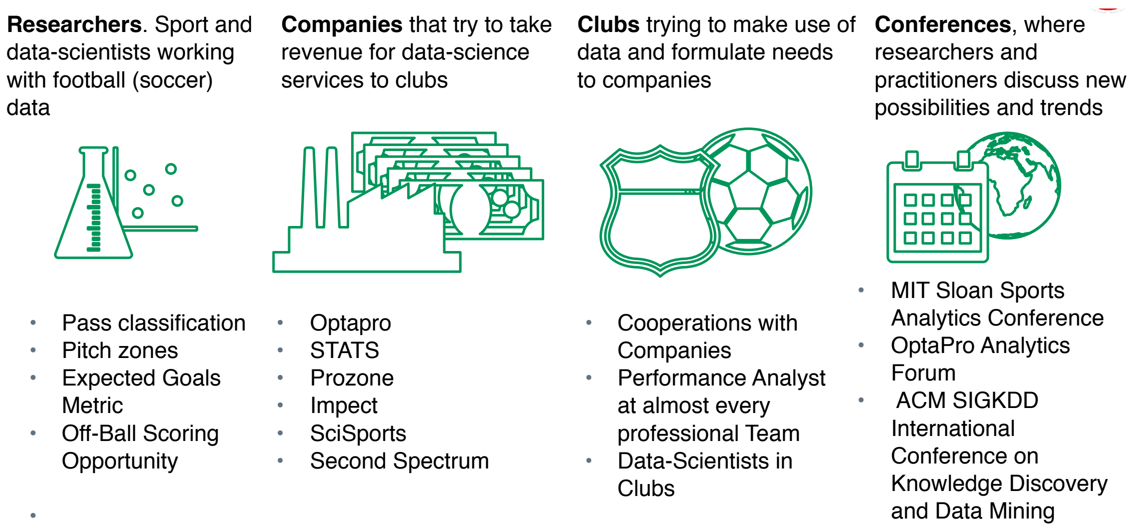

Figure 3: A collaborative effort between sports scientists, computer scientists, and football clubs will optimise the application of machine learning in a more relevant manner

Another issue about applying machine learning to football is the lack of a learning curve. Unlike other domains that build on previous findings, there has been a greater emphasis on trying to develop new, fancy approaches. This means that research in this field is more concerned with creating new machine learning approaches rather than incorporating existing approaches to build a better practice model. One example is the study by Goes et al. (F. R. Goes et al., 2018) that evaluated passing performance. They mentioned in their discussion section that their model would benefit from including the actual playing formation rather than the starting formations of a team, which could have been implemented using the findings of Bialkowski et al. (Bialkowski et al., 2016). From a methods standpoint, early research studies rarely validated their results with a test sample. Several studies had relatively small samples (some with just 1-2 games). With some exceptions (like expected goals), more recent studies have improved upon this and provide descriptions of their methods that allow for rebuilding their model and redoing their analysis. In doing so, practitioners can be sure that those approaches can be applied to new data sets and hold some predictive value, rather than overfitting the training data to show promising results within a publication.

One of the challenges for machine learning is to provide information about football beyond the capabilities of the human observer. For example, when Spatio-temporal data based on methods from computational geometry was used to create an approximation algorithm to identify pitch-dominant regions and rate the quality of passes in a football match, results indicated accuracy levels of 85.8% (Horton et al., 2015) and 90.2% (Chawla et al., 2017), an agreement between the machine classifier and a football expert observer similar in magnitude to the level of agreement between two observers. However, despite the accuracy between machine learning and human observers, analysts are still using observational notation analysis to study aspects of the game that machine learning has not yet been able to satisfy. For example, in studying the subtle behaviors that separate the top players from the rest, observational notation analysis was used to study English Premier League players´ visual exploration (moving their bodies and heads to enable perception of the full, 360 degrees of the external environment) in the 10 seconds prior to receiving the ball (Jordet, Bloomfield, & Heijmerikx, 2013). Results showed that players exhibiting a higher frequency of visual explorations are more consistent in completing passes to their teammates, especially midfielders making forward passes. If machine learning can measure these visual explorations combined with positioning data, it would save analysts´ time, amplify the amount of data that can be collected, and help teams find better playing solutions in specific match contexts.

Although positional data has improved, the machine learning algorithms need further refining, and the gap in analysing event data in unison with football theory needs narrowing (B Drust & M Green, 2013). To improve transferability to practice, mathematically based measures that are not the highest priority for coaches need to be simplified. The research should incorporate important aspects of football match performance that are not yet fully understood. These areas include team adaptability, communication, penetrating defensive lines, how possession is regained, and the effects of playing at varying tempos during different phases of the match (McLean et al., 2017).

3.5.2 Future directions of machine learning in football

As technology enhances analysts' ability to compare and value performance, more data continues to drive a revolution in football analytics. Machine learning is a new concept in football; more research is necessary to realize its potential to inform coaches and analysts practically. Further studies should aim to use larger samples and include both training and testing data sets to allow for feedback and model validation. In addition, providing clear descriptions of the steps of their approach and the methods section (or sharing via GitHub) will improve subsequent models and applicability.

If machine learning can decipher situations quickly and reliably, it would demonstrate a practical impact not yet apparent in the literature. There are also other pertinent questions related to football that machine learning can address in future research. Some of these questions include understanding more about how off-ball movement characteristics impact a team's decision-making and passing ability. Furthermore, information about how different defensive schemes influence ways of penetrating the defense is needed, including the constellations of players and off-ball movements that are most effective.

3.6 Conclusion

Most match analysis work has predominantly used simple descriptions and associations between variables. Moreover, advanced analyses have been driven by computer scientists and research-based approaches that lack practicality and adaptability by coaches and teams. Integrating machine learning with coaches and analysts in applied settings can account for many interacting variables, providing teams with practical information at faster speeds. However, relying on increasingly complex data analysis techniques will also present new challenges for future sports scientists. It is not only a matter of improving the machine learning techniques but the challenge of representing the knowledge in a way that can be understood and utilised in practice. This implies using multi-disciplinary approaches, including computer science research groups and sports scientists competent in football, to interpret the relevant value of the information and patterns produced by the machine.

Chapter 4: Attacking Key Performance Indicators in Soccer: Current Practice and Perceptions from the Elite to Youth Academy Level

This study has been accepted for publication following peer review. The content has been reformatted for this thesis. Full reference details for this study are:

Herold M, Kempe M, Bauer P, Meyer T. Attacking Key Performance Indicators in Soccer: Current Practice and Perceptions from the Elite to Youth Academy Level. J Sports Sci Med. 2021 Mar 1;20(1):158-169. doi: 10.52082/jssm.2021.158. PMID: 33707999; PMCID: PMC7919358.

4.1 Abstract

Key Performance Indicators (KPIs) are used to evaluate the offensive success of a soccer team (e.g., penalty box entries) or player (e.g. pass completion rate). However, knowledge transfer from research to applied practice is understudied. The current study queried practitioners (n=145, mean ± SD age: 36 ± 9 years) from 42 countries across different roles and levels of competition (National Team Federation to Youth Academy levels) on various forms of data collection, including an explicit assessment of twelve attacking KPIs. 64.3% of practitioners use data tools and applications weekly (predominately) to gather KPIs during matches. 83% of practitioners use event data compared to only 52% of practitioners using positional data, with a preference for shooting related KPIs. Differences in the use and value of metrics derived from positional tracking data (including Ball Possession Metrics) were evident between job role and level of competition. These findings demonstrate that practitioners implement KPIs and gather tactical information in a variety of ways with a preference for simpler metrics related to shots. The low perceived value of newer KPIs afforded by positional data could be explained by low buy-in, a lack of education across practitioners, or insufficient translation of findings by experts towards practice.

4.2 Introduction

In the domain of performance analysis in soccer, analyst and research teams support staff members with information primarily to enable understanding of performance, and to improve training regimes and decision-making. More specifically, many high-level soccer teams employ key performance indicators (KPIs) regularly to measure and increase tactical performance. KPIs are quantifiable measures used to evaluate the success of an organisation, team, employee, or athlete, in meeting objectives for performance. In soccer, KPIs have been combined with video analysis to inform practice (Groom, Cushion, & Nelson, 2011; Wright, Atkins, & Jones, 2012) and evaluate the success of a team (Jones et al., 2004; Ruiz-Ruiz et al., 2013) or player (Król et al., 2017). In recent years the complexity and predictive power of KPIs increased tremendously as several authors reported a direct link between offense-related KPIs and match performance in elite soccer (Matthias Kempe, Martin Vogelbein, & Stephan Nopp, 2016; Perl & Memmert, 2017; Yang, Leicht, Lago, & Gómez, 2018).

Despite these findings, there is a gap in knowledge transfer and usage between research and practice (Mackenzie & Cushion, 2013). This lack could be due to coaches primarily selecting KPIs based on their coaching philosophy and 'gut instinct' more so than the scientific literature (Wright et al., 2012). Another explanation could be that coaches favor qualitative methods such as subjective scouting reports (e.g. video analysis) over quantitative approaches (Nelson & Groom, 2012). In opposition to these preferences, there has been an exponential increase in the human capital invested in soccer research and analytics in recent years (F. Goes et al., 2020; Rein & Memmert, 2016b). This indicates that different stakeholders of a club or federation value, use, and implement KPIs differently. However, to date, no study has attempted to close or explain this gap between research and practice by investigating the perception and implementation of KPIs used by high-level soccer practitioners in their daily activities.

In principle, KPIs can be distinguished by their source of data being derived either from event data, positional data, or both. The use of event data, based on notational analysis, is a commonly used method to quantify and evaluate individual and team performance (Carlos Lago-Peñas & Dellal, 2010; Sarmento et al., 2014). Event data consists of individual actions (e.g. passes, shots, or tackles) assigned to one or more players. Basic measures such as frequencies, proportions, and other accumulated performance indicators of events happening throughout a match are commonly used in a team's evaluation process (Carlos Lago-Peñas & Dellal, 2010). Examples of such key behaviors include penetrating the defense (A. Tenga et al., 2017) and teams prioritizing the quick (10s or less) regain of ball possession (Kempe et al., 2014). KPIs gathered with event data have continued to evolve into higher value metrics such as expected goals (xG)(Lucey et al., 2014; Rathke, 2017), a predictive model used to assess every shot and the likelihood of scoring. Although event data are valuable in supporting tactical principles and identifying key game events;

they fail to account for temporal and spatial interactions of players and sequences of actions between teammates and opponents (Júlio Garganta, 2009; L. Vilar et al., 2012). An additional challenge of event data is coming to a global agreement on a standardised set of key performance indicators (Christopher Carling, Wright, Nelson, & Bradley, 2014), as experts often use slightly different definitions of the same event.

Technological advancements have led to new possibilities, allowing practitioners the ability to measure KPIs using automatic tracking systems, including video-based motion analysis, Global Positioning System (GPS) units (Christopher Carling et al., 2008) or Local Positioning Measurements (LPM) (W. G. Frencken, Lemmink, & Delleman, 2010). This concurrent technology integrated with data science approaches produces a range of variables enabling practitioners to quickly quantify actions on the pitch and create new KPIs and visualizations in greater detail (Herold et al., 2019; Perin et al., 2018; Z. Yue et al., 2008). By including time and space and/or player interactions, these KPIs enrich event data with context and provide evidence-based information to coaches and analysts (McLean et al., 2017; Memmert & Perl, 2009). For instance, Goes et al., (2019) combined xG with defensive pressure to create a *zone* metric for pass receivers that was significantly higher in winning teams compared to losing teams (F. Goes, Kempe, & Lemmink, 2019). Though soccer is a rather complex and unpredictable sport, the use of tracking data could accurately predict the match outcome in this study.

Whilst the quality of positional data has improved, there are still challenges around the precision of the information provided by tracking data relative to what is occurring on the pitch (Linke et al., 2018). Moreover, these mathematically based measures need further refining to be represented in a way that can be understood and utilized in practice (B Drust & M Green, 2013). Practitioners vary in their definition of success and might be interested in different indicators based on their preferred game style and formation (Meerhoff, Goes, & Knobbe, 2019; Memmert et al., 2017). Also, tactical analysis has increased in complexity (Rein & Memmert, 2016a) and the sophistication of KPIs has grown substantially since earlier key work on performance analysis (Nelson & Groom, 2012; Wright, Atkins, Jones, & Todd, 2013). Elite soccer clubs and federations consist of large backroom staff sizes (e.g. data scientists, performance analysts, strength and conditioning coaches, etc.) and tasks around performance analysis are widespread. Thus, there is a need for a more novel approach that provides a comprehensive overview of how diverse staff members from various levels of competition use and value KPIs. For example, it was expected that analysts at the professional level who specialize in tactical play would be more likely to use the modern and higher value KPIs compared to coaches or practitioners from levels where the outsourcing of tasks is not possible.

Although elite and professional teams have been reluctant to share information in the past, recent research has shown an increased willingness to facilitate the applications of those scientific findings (Ric et al., 2017). Accordingly, providing insight into the current practices and perceptions of KPI utilization will serve to highlight the challenges faced by practitioners and stimulate further industry-relevant applied research. Therefore, the current study aims to depict the status quo of attacking KPIs and provide a current perspective and practices in high-level soccer. To achieve this aim, a questionnaire of KPIs calculated based on event and positional tracking that are frequently mentioned in the literature or offered by commercial parties will be conducted. As defensive KPIs have not received extensive scientific attention thus far, the focus of this research remains on attacking parameters. The questionnaire will be shared with high-level coaches, assistant coaches, match analysts and scouts, and directors, to gain insight into the state of the art in the usage of KPIs.

4.3 Methods

4.3.1 Participants

The present research fully complies with the highest standard of ethics and participant protection which followed the guidelines stated in the Declaration of Helsinki (2013) and was approved by the Saarland University ethics committee. Following these guidelines, before completing the survey, participants received information about the purpose of the study and gave their informed consent for participation. A round of in-person pilot testing and a second-round online with thirty-five experts was performed prior to the beginning of the study to assess the face validity of each question. In addition, the pilot testing was used to ensure explanations provided for every KPI were understood. This was important as not every practitioner might be familiar with each KPI, or they may use different terminology within their club or federation. The survey was conducted online using Google Forms.

Participants were asked to specify their role as either a Director (technical director or director of coaching), Coach, Assistant Coach, Analyst, or Scout. Eligibility criteria specified that if the participant was a Director, Coach, or Assistant Coach, the respondent should have a minimum of a UEFA B License or the equivalent to be a representative of the final testing cohort. However, if the participant was an Analyst or Scout, it was unnecessary that they had a license. All Analysts and Scouts were included in the final cohort as many of these practitioners' do not have a coaching license, but a specific degree that varies broadly between federations. The level that participants worked was incorporated as an inclusion criterion. These included participants at the Federation level (men's national teams), the Professional level which included the top tier and second-tier league for each country (except the UK and Germany where the third and fourth leagues are considered professional, and Italy where the third league is considered professional), the Semi-Professional level, the Youth Academy level (the youth sector of top tier or second-tier professional clubs), and College soccer (NCAA[1] Division I and II). Based on these criteria, seven out of the 152 responses were excluded from the final analysis as they either did not meet the minimum requirements or failed to provide adequate information.

4.3.2 Procedure

An invitation to participate was e-mailed to a member of the coaching staff or match analysis department of each of the invited clubs from a personal network. The survey was uploaded to Google Forms. All responses were voluntary and anonymous. Respondents were provided with the link, and once a respondent had submitted the survey, they could not respond again. If no response was received within two weeks of the initial invitation, a second reminder email was sent. A third reminder email was sent in the event of no response after four weeks of the second message. If no response was received to the third message, a classification of "no response" was assigned.

Question development was guided with findings from a review of the literature exploring the most common KPIs differentiating between winning and losing teams, and expert experience from match analysts at the German Football Association (DFB = Deutscher Fussball-Bund). The inclusion of practitioner interaction ensured the validity of the questionnaire content (Stoszkowski & Collins, 2016). This approach followed the examples of other questionnaire development in football (Akenhead & Nassis, 2016; Weston, 2018; Wright et al., 2012).

The use of multiple-choice questions, checkboxes, and Likert scales have shown to be valid ways to gain insight into current practice and perceptions among football practitioners (Brink, Kuyvenhoven, Toering, Jordet, & Frencken, 2018; Weston, 2018). The Likert scale contained response labels as per Vagias (2006) (Vagias, 2006) and within the main part of the questionnaire, practitioners were asked to rank how strongly they agree or disagree about the value of different indicators using a 7-point Likert scale (with 1 being "strongly agree", 2 "agree", 3 "slightly agree", 4, "neutral", 5 "slightly disagree", 6 "disagree", and to 7 being "strongly disagree") and to what extent they use the indicator in their practice.

The survey was divided into three parts. First, participants were asked general questions about their role, country of employment, years of experience, age, level of competition, and coaching license. In the second part, they answered a block of questions on the general frequency of usage of KPIs (daily, weekly, monthly, or seasonally) and the availability and usage of digital (data) tools to gather event data, optical tracking data, and the use of wearable devices. The third and main part of the survey asked for the usage of each KPI and field of application (match analysis,

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[1] National College Athletic Association

training analysis, or both) followed by a ranking of twelve KPIs (see tables 1 and 2). The list included nine KPIs derived from event data and three KPIs gathered with positional tracking data. Two of the KPIs, Ball Possession Metrics and Pass Evaluation Metrics, each had sub-metrics that were further analysed.

Table 2: Definition of KPIs calculated based on Event Data and references linking them to success in soccer (references list up to the four most recent articles).

KPI	Definition	References
Total Shots	Shots (attempted) on the opposing goal, including shots that are not "on goal"	(Liu, Gomez, Lago-Peñas, & Sampaio, 2015), (Liu, Hopkins, & Gómez, 2016), (Alves et al., 2019)
Shots from Penalty Area	Shots attempted from within the penalty box area	(Wright et al., 2011), (Harrop & Nevill, 2014), (Liu et al., 2015)
Shots from Goal Box	Shots attempted from within the goal box ("6-yard box")	(Yiannakos & Armatas, 2006), (Armatas & Yiannakos, 2010), (Wright et al., 2011)
Shots on Goal	Shots on goal including goals. Excludes crossbar and goalpost contacts that do not lead to a goal	(F. M. Clemente et al., 2015), (Liu et al., 2015), (Alves et al., 2019)
Shooting Efficiency	The ratio of goals scored out of shots taken	(Zengyuan Yue et al., 2014), (Rathke, 2017)
Penalty Box Entries	An entry into the penalty area was defined by previous literature as an event that took place either when the team in possession of the ball passed it into the opponents' penalty area (regardless of whether the pass was received by a teammate) or when a player in possession of the ball went into that area of the pitch.	(A. Tenga et al., 2010b), (Ruiz-Ruiz et al., 2013), (Gómez et al., 2012),(Kite & Nevill, 2017)
Ball Possession Metrics	*Duration of Possession in a Game*: Sum off all times in ball possession of a team during a game	(Acar et al., 2008), (Collet, 2013), (Casal et al., 2017)
	Total Number of Passes In the Opponent's Half: Completed passes within the offensive team prior to a) the ball going out of play; b) the ball touches a player of the opposing team (e.g. by means of a tackle, an intercepted pass or a shot being saved). A momentary touch that does not significantly change the direction of the ball is excluded; c) an infringement of the rules takes place (e.g. a player is off-side, or a foul is committed).	(Harrop & Nevill, 2014), (Kite & Nevill, 2017)
	Total Number of passes completed per game: The sum of all completed passes	(Pena & Touchette, 2012)
	Passing Networks: Networks are constructed from the observation of the ball exchange between players. Network nodes are players and links account for the number of passes between any two players of a team.	(Pena & Touchette, 2012), (Grund, 2012; Gyarmati, Kwak, & Rodriguez, 2014), (McHale & Relton, 2018)
Crosses	A cross constitutes as a pass from the wide area of the pitch between the edge of the goal box and the sideline that travels into a more central area in the penalty box.	(Joseph B Taylor, Mellalieu, James, & Shearer, 2008), (Carlos Lago-Peñas & Dellal, 2010), (Mitrotasios & Armatas, 2014), (Sarmento et al., 2014)
Expected Goals	Expected goals is a predictive model used to assess every shot, and the likelihood of scoring. A xG model computes for each chance (shoot on goal) the probability to score based on what we know about it (event-based variables). The higher the xG - with 1 being the maximum, as all probabilities range between 0 and 1, the higher the probability of scoring.	(Lucey et al., 2014), (Ruiz et al., 2015), (Eggels & Pechenizkiy, 2016), (Rathke, 2017)

PI	Definition	References
Expected Possession Value	The expected outcome (likelihood to score a goal) at every moment in a possession based on positional tracking data.	(Fernández, Bornn, & Cervone, 2019)
Space Control	Control of space between an attacker and defender is estimated using Voronoi-diagrams (Voronoi diagram is a partitioning of a plane into regions based on distance to points in a specific subset of the plane) based on the player's position on the pitch.	(Fujimura & Sugihara, 2005), (Memmert et al., 2017), (Rein & Memmert, 2016b), (Rein et al., 2017)
Pass Evaluation Metrics	*Packing* (Measures the number of opponents a pass outplays based on the longitudinal coordinates) between the time of the pass and reception. For defenders, it only includes last 6 players on the field plus the goalkeeper based on the longitudinal coordinates or how many players are overplayed in terms of distance between the ball and the center of the opponent's goal.	(Memmert et al., 2017), (Rein et al., 2017), (F. Goes et al., 2019), (Steiner, Rauh, Rumo, Sonderegger, & Seiler, 2019)
	D-Def (measures the disturbance a pass causes on the defense)	(F. R. Goes et al., 2018), (Kempe & Goes, 2019)
	I-Mov (the movement of all opposing players in response to a pass)	(F. R. Goes et al., 2018), (Kempe & Goes, 2019)
	Pass Completion Percentage: The percentage of completed passes versus incomplete passes	(Redwood-Brown, 2008), (McHale & Relton, 2018)
	Pass Risk/Reward: i) Risk – the likelihood of executing a pass in each situation, and ii) reward – the likelihood of a pass creating a chance	(Power et al., 2017), (McHale & Relton, 2018)

4.3.3 Statistical Analysis

Chi-square tests were utilised to examine differences between roles ("Coach" versus "Assistant Coach" versus "Analyst and Scouts" versus "Directors") and levels of competition ("Federation" versus Professional" versus "Semi-Professional" versus "Youth Academy" versus "College") for the specific use of the KPIs. Next, to examine differences between roles and levels of competition for KPI rankings there were outliers in the data as assessed by inspection of a boxplot. Therefore, it was determined a Kruskal-Wallis H Test would be more appropriate. Using a Krustal-Wallis H Test for level of competition and KPI rankings, pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. Values are mean ranks unless otherwise stated. Based on Ferguson's recommendations for effect size, strength of association indices (e.g., Cramer's V for chi-square and ε^2 for Kruskal-Wallis H Test) were considered practically significant when $V \geq .20$ and $\varepsilon^2 \geq .04$ (Ferguson, 2009).

4.4 Results

4.4.1 Background of Practitioners

In total, 145 participants (mean ± SD age: 36.2 ± 9.3 years) completed the survey. Subsequently, survey respondents included 42 different countries with most of the participants from the USA (26) and Germany (16), followed by England (10), Portugal (10), Italy (8), and the Netherlands

(7). Coaches represented the largest sample followed by Analysts and Scouts, with almost half of all participants working at the Professional level. (See Table 3).

Table 3: Practitioner breakdown by Level of Competition and Role

		Level of Competition					
		Federation	**Professional**	**Semi-Professional**	**Youth Academy**	**College**	**Total**
Role	**Analysts and Scouts**	6	25	5	5	0	**41**
	Assistant Coach	0	14	3	3	2	**22**
	Coach	3	29	8	28	5	**73**
	Director	3	2	0	4	0	**9**
	Total	**12**	**70**	**16**	**40**	**7**	**145**

4.4.2 Use of Technology

4.4.2.1 General Use of Data Tools

Of the listed data tools and applications, 37% of participants reported no use, while 17% use tools and applications not listed (e. g. Longomatch[2]). Differences between roles for the use of different data tools and applications were significant (p=.04, V=.41). Although no statistically significant difference (p=.22) was found between levels of competition, a moderately strong association and practical significance (V=.37) was found. 63% of Semi-Professionals and 40% of Youth Academy practitioners reported no use of data tools and applications at all compared to just 33% of Federation, 30% of Professionals, and 29% of College practitioners.

4.4.2.2 Metrics/KPIs Based on Event Data

Overall, 83% of participants reported the use of event data technology. 35% of participants reported using their own tagging using platforms such as Hudl or Sportscode rather than relying on external sources such as Stats Perform[3], or official league sources such as Bundesliga Event Data. There was a significant difference (p=.006, V=.30) between level of competition for the use of KPIs derived from event data with practitioners from Federations and the Professional level reporting greater use. There was no significant difference (p=.38, V=.21) between roles for the use of event data technology.

[2] https://longomatch.com/en/

[3] http://statsperform.com

4.4.2.3 Metrics/KPIs Based on Optical Positional Tracking

Among the practitioners using optical positional tracking data, there was no evidence of one preferred tool. Over half of the participants (75=52%) did not use any positional tracking regularly. No significant differences between role (p=.38, V=.26) or level of competition (p=.70, V=.23) for the use of positional tracking were found. However, findings showed small levels of practical significance for both with a trend for greater use at higher levels.

4.4.2.4 Metrics/KPIs Based on Wearable Technology

67% of participants reported the use of wearable technology. Catapult[4] (19%) and STAT Sports[5] (19%) were the most commonly used wearable devices. The differences between roles for the use of wearable technology approached significance (p=.055, V=.34), and there was no significant difference between levels of competition for the use of wearable technology (p=.25, V=.30). Differences for both role and level of competition showed small practical significance.

4.4.3 Frequency of KPI Use

The most utilized KPIs were related to shooting, whilst the least used were the passing and possession-based metrics that depend on positional tracking (see Figure 5). Almost half of the participants (45%) reported the use of KPIs on a weekly basis, although 58% of practitioners from the Federation level reported using KPIs daily (Figure 4). This may reflect the different scheduling between national versus club teams.

[4] http://catapultsports.com.de

[5] http://statsports.com

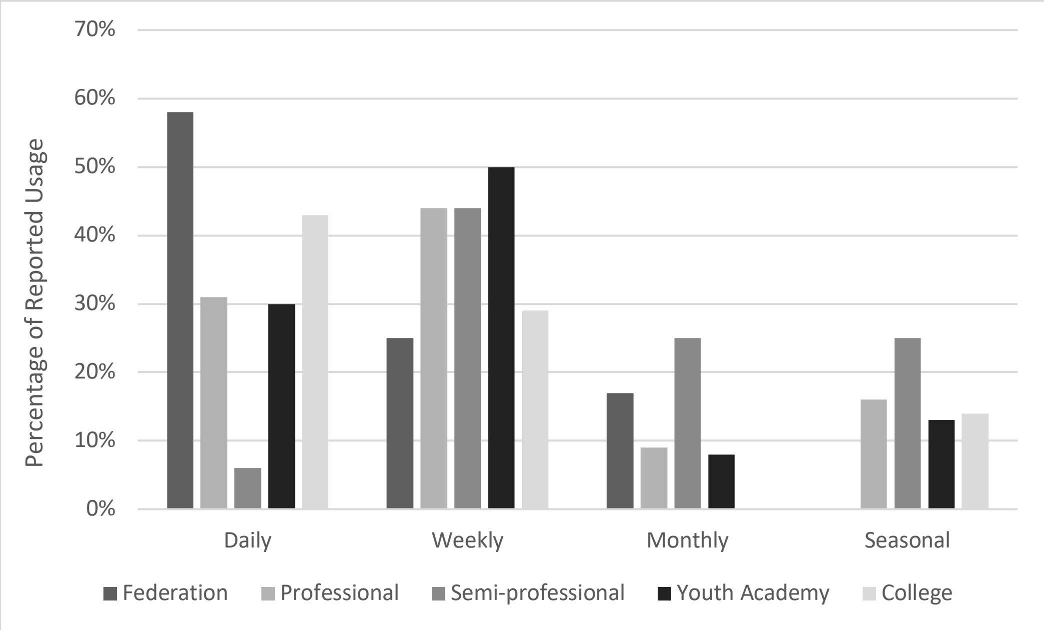

Figure 4: Frequency of KPI use between levels of competition

4.4.4 Use of KPIs for Matches, Training, or Both Training and Matches

It was reported that 35% of practitioners use KPIs for matches, while 19% use them for both training and matches, and only 3% for training alone. Significant differences were only found between roles for Ball Possession Metrics (p=.04, V=.20) and Pass Evaluation Metrics (p=.04, V=.20). There were no significant differences found between levels of competition (p=.07 to .99, V=.11 to .23).

4.4.5 Use and Value of the Different KPIs

The five most used KPIs were Shots on Goal (77%), Shots from Penalty Area (73%), Total Shots (70%), Crosses (70%), and Shooting Efficiency (68%). The bottom five KPIs included Shots from the Goal Box (57%), xG (46%), Pass Evaluation Metrics (44%), Space Control (33%), and Expected Possession Value (22%).

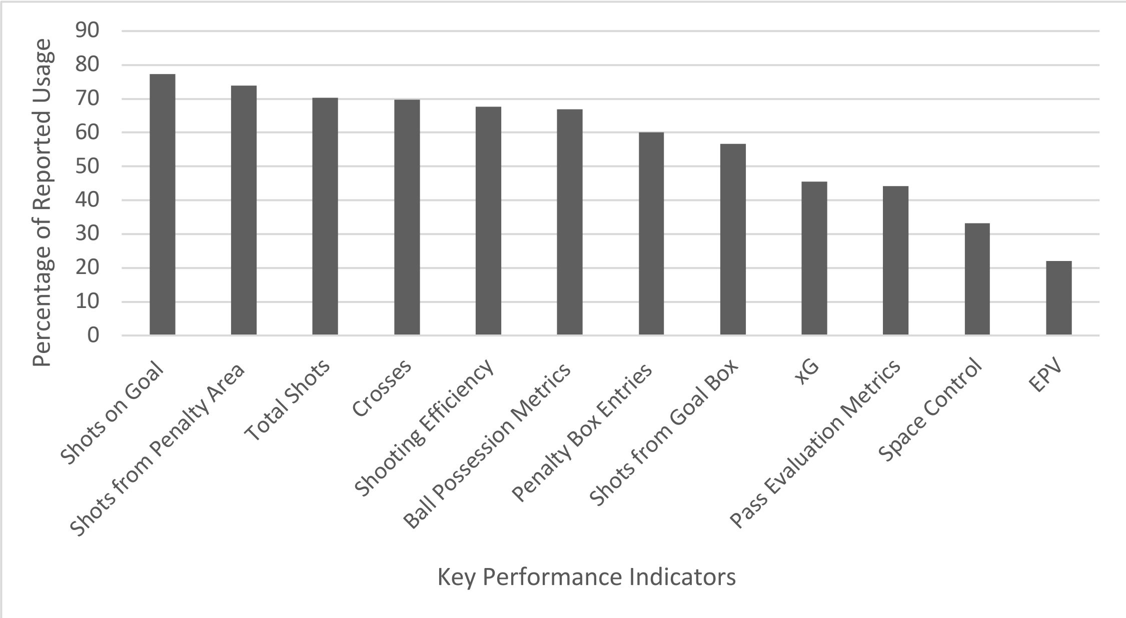

Figure 5: Frequency of use between KPIs

Overall, rankings ranged between 2.6 and 3.4 on the Likert scale with no single KPI standing out from the rest. The top five valued KPIs were: Shots from the Penalty Area (2.6), Pass Evaluation Metrics (2.7), Shots on Goal (2.8), Shooting Efficiency (2.8), and Crosses (2.8). The lowest five valued KPIs were Shots from the Goal Box (2.9), xG (3.2), Ball Possession Metrics (3.2), Expected Possession Value (3.3), and Total Shots (3.4).

4.4.5.1 Differences between Roles for the use of KPIs

Chi-square tests revealed no significant difference between roles and KPI use except for the use of Pass Completion Percentage (p=.02, V=.26) and Pass Accuracy in the Opponent's Half (p=.01, V=.29). For Pass Completion Percentage, 37% of Analysts and Scouts and 40% Coaches reported using it while only 9% of Assistant Coaches and 11% of Directors reported use. Regarding Pass Accuracy in the Opponent's Half, 16% of Assistant Coaches use it compared to just one Analyst and Scout out of the rest of the entire sample of participants. Analysts and Scouts reported using some metrics more frequently than other groups, including 73% using Ball Possession metrics, with 48% of Analysts and Scouts using Passing Networks and 61% Total Passes per Game. Analysts and Scouts also used Space Control (39%) and Pass Evaluation Metrics (51%) more often than the other groups. However, only 20% of Analysts and Scouts reported using Expected Possession Value vs. 26% of Coaches.

4.4.5.2 Differences between Levels of Competition for the use of KPIs

There was a significant difference (p<.001, V=.61) between levels of competition for the use of KPIs, ranging from Shots on Goal (p<.001, V=.42) to Passing Networks (p<.001, V=.74). Notably, practitioners from the higher levels including Federations and Professionals relied more on Expected Goals and Ball Possession Metrics than practitioners from the lower levels.

Table 4. Difference between levels of competition and use of KPIs.

	Total Shots	Shots from the Penalty Area	Shots from the Goal Box	Shots on Goal	Shooting Efficiency	Penalty Box Entries	Crosses	Ball Possession Metrics	xG	EPV	Space Control	Pass Eval Metrics
Federation	75%	67%	58%	83%	67%	42%	67%	75%	50%	17%	33%	42%
Professional	74%	67%	54%	77%	70%	69%	73%	80%	59%	29%	37%	53%
Youth Academy	63%	78%	63%	80%	65%	55%	70%	57%	35%	18%	35%	35%
Semi-Professional	75%	76%	63%	75%	69%	56%	75%	50%	31%	19%	19%	38%
College	57%	57%	29%	57%	57%	43%	29%	50%	0%	0%	14%	29%

4.4.5.3 Use of Specific Ball Possession Metrics

Sub-categories were created for Ball Possession Metrics and Pass Evaluation Metrics. For Ball Possession Metrics, Total Passes Per Game was used most (49%) followed closely by Total Passes in the Opponent's Half (47%), Total Duration of Possession (46%), and Passing Networks (40%). Pass Accuracy in the Opponent's Half was only used by 3% of participants.

There was lower reported use for Pass Evaluation Metrics. Pass Completion Percentage was used the most (24%), followed by *Packing* (22%) and Pass Risk/Reward (17%). I-Mov was used by 10% of the participants, while D-Def was a mere .3%.

4.4.5.4 Differences Between Roles for KPI Rankings

The distribution of scores was not similar between roles for the value of different KPIs. Shots from the Penalty area were valued highest among all roles except for Directors. Although there was a slight pattern that Directors favoured Expected Goals (xG) and Analysts and Scouts favoured Pass Evaluation Metrics and Space Control, the Krustal-Wallis H test did not yield significant differences between groups (values ranging from p=.12, ε^2=.04 for Space Control, to p=.99, ε^2=.00 for Shots on Goal).

4.4.5.5 Differences between Levels of Competition for KPI Rankings

Only Penalty Box Entries (p=.04, ε^2=.07) and Space Control (p=.02, ε^2=.08) showed significant differences between groups. However, in support of the small effect sizes, Bonferroni post hoc analysis revealed no statistically significant differences between levels of competition for Penalty Box Entries or Space Control. None of the levels placed a high value on Total Shots, but Shots from the Penalty Area was valued favourably across all levels. Youth Academy Practitioners valued Space Control the highest while Semi-Professional and College practitioners valued Pass Evaluation Metrics the highest.

Table 5. Smaller numbers designate higher rankings. 1 represents the highest ranking while 7 represents the lowest.

	Total Shots	Shots from the Penalty Area	Shots from the Goal Box	Shots on Goal	Shooting Efficiency	Penalty Box Entries	Crosses	Ball Possession Metrics	xG	EPV	Space Control	Pass Eval Metrics
Federation	4.25	2.75	3.5	3.08	2.92	4.08	3.25	3.5	3.25	3.67	4.17	3.5
Professional	3.31	2.49	2.81	2.7	2.69	2.47	2.51	2.85	2.99	3.12	2.71	2.44
Youth Academy	3.28	2.5	2.92	2.54	2.62	2.74	2.99	3.18	3.23	3.31	2.49	2.86
Semi-Professional	3.94	3	3	3.06	3.31	3.5	3.31	4.13	3.44	3.75	3.25	2.81
College	3.86	3.29	3.86	3.29	3.29	3.43	3.43	3.16	3.66	3.67	3.29	3
Total	**18.64**	**14.03**	**16.09**	**14.67**	**14.83**	**16.22**	**15.49**	**16.82**	**16.57**	**17.52**	**15.91**	**14.61**

4.5 Discussion

The aim of the present study was to gain insight into current use and perceptions of different technologies and KPIs for measuring (tactical) performance in soccer. Compared to previous surveys, this novel approach consisted of a larger sample of diverse staff members from different levels including more top-level coaches (Akenhead & Nassis, 2016; Brink et al., 2018; Wright et al., 2012; Wright et al., 2013). The main findings of this study are that there are a variety of ways practitioners gather information and use and value both simple (e.g. Shots on Goal) and more sophisticated metrics (e.g. xG, EPV) for tactical analysis. Some of the differences are determined by the level of competition and the role of a practitioner within a club. The implementation and perceived value of newer KPIs offered by optical positional tracking technology was lower than anticipated. As suggested by previous findings (Brink et al., 2018), this could be explained by a financial restraint within clubs or skepticism towards the soccer-specific knowledge of a data scientist. Furthermore, these complex KPIs are often only published in scientific journals or presented at scientific conferences which may influence a lack of education and awareness among practitioners.

4.5.1 Use and Granularity of Available Data

As expected, a greater percentage of practitioners at the higher levels of elite soccer (approximately 70%) reported using data tools and applications compared to practitioners at the Youth Academy (60%) and Semi-Professional (37%) level. These findings resonate with the fact that data are acquired consistently by professional leagues (Pappalardo et al., 2019) and provided to clubs and federations (Brud, 2017). Although lower-tier clubs with limited funding (Setterwall, 2003) can purchase relatively low-cost GPS units instead of the high-price optical tracking to use several of the data tools, they might still lack the personnel to incorporate them. This could also explain the significant difference found between the use of event data technology and level of competition, with lower use evident in the Semi-Professional and Youth Academy levels. However, these results were still surprising as basic notational analysis can be performed with a normal camera and software (e.g. Hudl, Sportscode). Also, KPIs measured with such a setup are used on a wide basis in the media and coaching education. Therefore, one can assume a lack of buy-in to quantitate analysis of tactical performance in general by this peer group.

The use of event data (83%) was more common than the use of optical positional tracking (75%). Along with higher monetary costs, this is possibly due to recent developments using positional tracking for tactical analysis and hence, a lack of familiarity amongst practitioners (Rein & Memmert, 2016a). In addition, positional tracking contains considerably more information. Thus, the aggregation of larger amounts of data into reasonable insights such as the interpretability of the underlying models requires greater refinement. Whereas data-science research often aims to derive new KPIs to understand tactical performance, this investigation supports earlier findings that there is a need to better simplify and visualise available KPIs in a straightforward way to coaches and practitioners (Christopher Carling et al., 2014). Otherwise, advanced KPIs and information provided by data-scientists and companies are not seen as an added value to practitioners. Moreover, approximately one-third of the participants (36%) rely on their own tagging to gather information. Practitioners may not trust the automated data provided by optical tracking technology and companies, or it fails to cover all of their needs. Interestingly, only 80% of practitioners from the professional level reported using wearable technology. This may reflect the fact that clubs rely on league-wide tracking (e.g. Stats, Tracab) during matches but depend more on wearable technology for training sessions. This supports a similar trend by the sports medicine and sports science departments of professional clubs who reported greater use of wearable technology for physiological data (and not tactical purposes) in training sessions compared to matches (Akenhead & Nassis, 2016).

4.5.2 Use and Value of KPIs

This survey revealed that KPIs are mostly used to analyse matches of a team weekly rather than monitoring training sessions. In addition to possible lack of time and interest by practitioners, there are technical and physical differences between training sessions and matches and that could justify the lower use of KPIs in training (Olthof et al., 2019). For instance, compared to 11 vs 11 training games, players in official matches completed fewer passes per minute and displayed more errors in passing, but covered greater distance and performed more sprints. However, while technical and physical parameters differ significantly, tactical performance is rather unaffected if comparing 11 vs 11 training games to official matches (Olthof et al., 2019). Given these findings, it might be beneficial to monitor tactical performance and close the gap between data used in matches and training. As several amateur and professional teams employ the use of small-sided games in training sessions (Halouani, Chtourou, Gabbett, Chaouachi, & Chamari, 2014; Sarmento, Clemente, Harper, et al., 2018), researchers could scale KPIs to varying field dimensions and/or coaches can use variables that have a global meaning such as space control (Fernandez & Bornn, 2018) or defensive pressure (Andrienko et al., 2017). This could help evaluate a specific tactic or formation used in training as KPIs vary between formations in build-up play (Memmert, Raabe, Schwab, & Rein, 2019).

Principally, practitioners preferred rather simple KPIs based on event data with Shots on Goal as the best rated. As practitioners focus on these outcome (goal) related KPIs rather than process-related ones, it is even more understandable that they might not see the value in using KPIs during training. Aside from shooting-related KPIs, analysis of the specific Pass Evaluation Metrics showed Pass Completion Percentage was used the most, whilst more recently developed metrics based on optical tracking such as I-Mov, D-Def, and Pass Risk/Reward were used the least. Nonetheless, the average use of Pass Completion Percentage was still only 24% across all practitioners. Despite receiving media attention and research validating the concept of outplaying opponents (Rein et al., 2017), the use of *Packing* was only 22%. Regardless of the apparent lack of interest by practitioners, the evaluation of passing performance such as extrapolating styles of play (Bialkowski, Lucey, et al., 2014a; Gyarmati et al., 2014) and placing value on specific passes (Bransen, Van Haaren, & van de Velden, 2019), remains a common focus by researchers using tracking data. However, the results of this study suggest a possible disconnect between research on tactical play and applied practice.

One area of soccer that has been well researched is ball possession, with several studies based on event data having shown ball possession is linked to team success (Casal et al., 2017; Jones et al., 2004). In line with this, nearly half of practitioners (48%) reported usage of the more easily computed ball possession KPIs such as Total Duration of Possession. However, there was a clear distinction between roles as Analysts and Scouts reported using newer metrics (e.g Space Control) dependent upon positional data more often than Coaches, Assistant Coaches, and Directors. Analysts' and Scouts' implementation of more complex methods highlights their task within the team as well as the growing use of technology to enhance the feedback process in coaching (Rein & Memmert, 2016a; Wright et al., 2012). Nonetheless, there is a gap between work being done in computer science and the focus of analysts and scouts in a practical setting. Advances to improve data comprehension and reporting to the analysts and ultimately the coaching staff have begun with clubs and federations such as the German Football Association (DFB = Deutscher Fussball-Bund) hiring a data scientist. Furthermore, events such as hackathons[6,7] and the Barcelona Innovation Hub[8] function to educate coaches and analysts. Although clubs and federations are taking steps to meet this demand, as highlighted in this analysis, it will likely require further time and support to be adopted by semi-professional and youth levels.

Besides the reported frequency, there were also differences in the importance placed on various KPIs per role. Other than their affinity for Expected Goals (xG), Directors' overall ranking of KPIs was lowest compared to other roles. The perceived low value of KPIs by Directors was unexpected as it is often the function of the technical and/or coaching director to work with data to oversee and improve broad aspects of performance (Kasap & Kasap, 2005). Perhaps including a greater number of participants in the Directors group would have revealed higher value for KPIs, and presumably, the increase of data-driven approaches will start influencing the perspective of practitioners in these managerial positions. Compared to Assistant Coaches and Directors, Coaches and especially the Analysts and Scouts gave higher value to metrics relying on positional data including Pass Evaluation Metrics and Space Control, while devaluing Expected Goals (xG). Head coaches placing a higher value on complex metrics than Assistants was an unexpected finding, possibly representing a trend for Assistant Coaches to carry out the training sessions while Head Coaches communicate more often with the Analysts and Scouts. This gives Analysts and Scouts the chance to negotiate the use of KPIs with the coach to reflect the coach's philosophy, strategy, and tactics (Wright et al., 2013).

In general, across roles and levels of competition, practitioner's responses revealed interest in the ability to evaluate passes. In contrast, the results revealed minimal use of more recent metrics (e.g.

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[6] https://www.dfb-akademie.de/hackathon-2-sts-akademie-eintracht/-/id-11009109

[7] https://www.ussoccer.com/official-us-soccer-hackathon

[8] https://barcainnovationhub.com/

D-Def, Expected Possession Value) and the continued reliance on traditional methods of assessments in their practice. Other than goal-scoring, no gold-standard measure of soccer performance exists. Thus, practitioners turn to methods comprehensible to them to improve understanding of player and team performance. Furthermore, coaches primarily rely on coaching clinics and seminars with fellow coaches to further their development (Brink et al., 2018; Stoszkowski & Collins, 2016). These cultural and social influences on performance analysis must be considered in the promotion of new approaches (Groom et al., 2011) and perhaps coaching courses present an opportunity to bring awareness to coaches about data and analytics. Furthermore, Brink et al. (2018) reported that coaches appear most convinced about their tactical knowledge. They see this as their field of expertise, which might be the reason for a low buy-in into metrics that could from their perspective, challenge their position and authority. Therefore, continuing education provided to practitioners about the capabilities of new tracking technology is required.

Before coaches and analysts start adopting newly available methods of analysing performance, another challenge to overcome is coaches' perception that the scientists conducting research lack specific soccer knowledge (Brink et al., 2018). Furthermore, without the burdens of tedious statistical analysis and the publication process, 'fast-moving practitioners' more often rely on their knowledge and expertise to come up with new ideas and training methods before they can be validated (Coutts, 2016). Despite the push for greater use of quantitative methods to objectify the game, qualitative analysis is still at the crux of what coaches do (Nelson & Groom, 2012). Training methods and tactics continuously evolve around the use of space, time, and individual actions to win soccer games (Júlio Garganta, 2009). Along these lines, coaches' input should be prioritized in the development of KPIs which represent success in the context of play. This includes knowledge about specific players, various playing styles, and making comparisons between opposing teams (Meerhoff et al., 2019). As such, one limitation of our study is the lack of KPI normalization. Thus, further studies could investigate how practitioners' use of KPIs change depending on specific factors such as the strength of the opposition, the score line, or whether it was a home or away game.

Despite the problems associated with KPI-driven science and practice, there has been a recent rise in the synergy between domains including the presence of coaches and analysts involved in research. For instance, the work by Link et al. (2016), Rein et al. (2017), and Goes et al. (2018) serve as examples of sports science in which new features were developed and validated to assess tactical performance. Though predominately more from a computational perspective, work by Power et al. (2017), Spearman et al. (2017) Andrienko et al., (2017), and Fernandez and Bornn (2018) still involved domain expertise from soccer. The ability to evaluate passes based on the likelihood of a pass creating a scoring chance versus being intercepted (Power et al., 2017), and measuring the probability that a player currently not in possession of the ball will score (Spearman, 2018), transcend data science and speak practitioners' language. These efforts represent progress, but collaboration and education between practitioners and scientists must continue to go both ways. The interplay between computer science experts who can handle the vast amounts of data, and domain experts who can address the right questions, is a challenging task (F. Goes et al., 2020). Increased multi-disciplinary approaches including research groups and sports scientists competent in soccer will continue to be necessary to optimise KPI development and application. This includes the continued integration of data-scientists or data-literate match analysts embedded within the staff of clubs and federations. Future work should not be limited to developing more advanced KPIs but conduct intervention studies to further elucidate how already available KPIs can be used by practitioners in training as well as matches. Greater coach and analyst involvement in the research and development process increases the buy-in and the likelihood practitioners will interpret the relevant value of the information. In turn, this may improve the training process as well as performance on the pitch.

4.6 Conclusion

This study provides novel findings that demonstrate practitioners' perception and implementation of key performance indicators. The results showed that most practitioners who participated in this survey see value in, and commonly use, technology in their tactical analysis and KPIs. Respondents reported greater use of event data (83%) and wearables (67%), while the use of position tracking data (52%) is still lagging. The low use of tracking data was also evident in the reporting of KPI usage and ranking, as practitioners most frequently use shooting related metrics that are gathered with event data (Shots on Goal, Shots from Penalty Area, Total Shots, Crosses, and Shooting Efficiency). Other than Pass Evaluation Metrics, which was ranked high despite low reported use, a similar trend was noted in their ranking of KPIs (Shots from the Penalty Area, Pass Evaluation Metrics, Shots on Goal, Shooting Efficiency, and Crosses). As some KPIs relying on tracking data show promise in the speed and quality of information they can provide, improvements in applied research, collaboration, and educational and financial resources are necessary. The integration of tactical KPIs into the training process and combined efforts between practitioners and researchers in the form of intervention studies are recommended. Further understanding practitioners' performance goals and preferred methods of analysis could help toward implementing strategies to optimise the implementation of these newer methods of analysis into practice.

4.7 Acknowledgements

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Chapter 5: Off-Ball Behaviour in Association Football: A Data-Driven Model to Measure Changes in Individual Defensive Pressure

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5.1 Abstract

This study describes an approach to evaluate the off-ball behaviour of attacking players in association football. The aim was to implement a defensive pressure model to examine an offensive player's ability to create separation from a defender using 1411 high-intensity off-ball actions including 988 Deep Runs (DRs) DRs and 423 Changes-of-Directions (CODs). Twenty-two official matches (14 competitive matches & 8 friendlies) of the German National Team were included in the research. To validate the effectiveness of the pressure model, each pass (n=25,418) was evaluated for defensive pressure on the receiver at the moment of the pass and for the pass completion rate (R=-.34, p<.001). Next, after assessing inter-rater reliability (Fleiss Kappa of .80 for DRs and .78 for CODs), three expert raters notated all DRs and CODs that met the pre-set criteria. A time-series analysis of each DR and COD was calculated to the nearest 0.1 second, finding a slight increase in pressure from the start to the end of off-ball actions as defenders reestablished proximity to the attacker after separation was created. A linear mixed model using run type (DR or COD) as a fixed effect with the local maximum as a fixed effect on a continuous scale resulted in $p < 0.001$, $d = 4.81$, CI = 0.63 to 0.67 for the greatest decrease in pressure, $p < 0.001$, $d = 0.143$, CI = 9.18 to 10.61 for length of the longest decrease in pressure, and $p < 0.001$, $d = 1.13$, CI = 0.90 to 1.11 for the fastest rate of decrease in pressure. As these values pertain to the local maximum, situations with greater starting pressure on the attacker often led to greater subsequent decreases. Further, there was a significant (p<.0001) difference between offensive and defensive positions and the number of off-ball actions. Results suggest the model can be applied to quantify and visualize pressure exerted on non-ball-possessing players. This approach can be combined with other methods of

match analysis, providing practitioners with new opportunities to measure tactical performance in football.

Keywords: soccer, performance analysis, data science, off-ball behaviour

5.2 Introduction

In association football, it seems that some players simply have a “knack” for being in the right place at the right time. The German attacking player Thomas Müller, for example, is often characterized as the “Raumdeuter”, or “space interpreter”, because of his ability to use unique running patterns without the ball to create space where it seems there should be none (Rice-Coates, 2017). Defenders are a constraint in which attacking players must instigate and adjust their running behaviour to afford themselves the time and space to better execute various skills (Davids, Araújo, Hristovski, Passos, & Chow, 2012; Orth, Davids, Araújo, Renshaw, & Passos, 2014). Although experts can point out such exceptional tactical behavior, the community lacks a reliable method to evaluate movement away from (off) the ball (Herold et al., 2019). While there are several options to evaluate a player’s performance with the ball, a tool to measure the importance of a player like Thomas Müller for his ability to alleviate pressure (a reduction of space between the attacker and the defender), is missing. To close this gap, this study uses a modified approach from Andrienko et al. (2017) developed for pressure on the ball carrier and attempts to demonstrate its usefulness as a tool to evaluate a player’s behaviour off the ball (Andrienko et al., 2017).

In recent years, technological developments including automatic tracking systems, video-based motion analysis, and Global Positioning System (GPS) units (Christopher Carling et al., 2008) have facilitated the process of evaluating player (tactical) performance in a match (Rein & Memmert, 2016a). To date, most of the studies evaluating tactical behaviour using positional tracking data have focused on events or actions by the player with the ball, such as passing (Alves et al., 2019). One example of such a study is the work by Chawla et al., (2017) , who used the position, velocity, and acceleration of all twenty-two players and the ball to determine the probability of a pass reaching the intended receiver based on inferences made by an observer (Chawla et al., 2017) . The work of Steiner and colleagues provides even further information about the influence of the recipient’s position and an open passing lane has on the decision to play a pass (Silvan Steiner, 2018). Although these studies provided insight into players’ decisions and performance with the ball, they did not present implications on how teammates can provide better passing options by finding uncovered space or creating distance between themselves and the nearest defenders.

To understand how offensive players create space, a player’s behaviour should be examined as a dynamic interaction including the task, time, and space relative to the opponent (Grehaigne et al., 1997). Researchers have come up with variables such as team centroid (average team position), demonstrating that football teams move in synchrony in the latitudinal and especially, the longitudinal direction (Duarte et al., 2012; Frencken, Lemmink, Delleman, & Visscher, 2011). However, closer inspection is required to identify how disruptions in inter-team synchronicity influence the occurrence of key events like shots or goals. As such, studies began examining defensive pressure from a collective level (e.g., game styles, collective movement). For example, Fernandez-Navarro et al. (2016, 2018) evaluated how a team's style of play including the use of high pressure and playing tempo changed depending on match status, venue, and quality of opposition (Fernandez-Navarro et al., 2016) (Fernandez-Navarro, Fradua, Zubillaga, & McRobert, 2018). While findings point to the importance of the attacker breaking symmetry from the defender (distance and angle relative to the goal) to gain a positional advantage, there is still a lack of understanding about how offensive players, including those without the ball, create separation from defenders.

New developments in spatio-temporal data research made it possible to contextualize positioning of defending and attacking players, thereby facilitating the calculation of real-time probabilities of offensive success relative to defensive presence (for an overview see Goes et al., 2020 and Herold et al., 2019), and the subsequent evaluation of performance and decision-making (F. Goes et al., 2020) (Herold et al., 2019). This idea was first introduced in basketball (Cervone, D'Amour, Bornn, & Goldsberry, 2014) and then adapted to football by combining variables such as playing zone, defensive pressure, shot density, and pass density to form a new metric called *Dangerousity* (Link et al., 2016). This idea of constantly measuring the defensive pressure on the ball carrier was picked up by several other research groups. For example, Andrienko et al., (2017) created a method based on a spherical figure around the ball-possessing player (Se), with any opponent entering this zone applying a certain amount of pressure on the player depending on his vicinity to the player and whether he's in front or behind him (Andrienko et al., 2017). Although this method is more elaborate than the one used by Link and colleagues, it was only validated in five games with a focus on the ball carrier. These examples illustrate that approaches exist that could be adapted to evaluate off-ball behavior; however, this transfer has not yet been made. Therefore, the present study aims to check the feasibility of a model for the visualization and quantification of defensive pressure of players off the ball. Such a tool could be helpful to evaluate the decision made by a passer and the behaviour of (potential) pass recipients.

In this work, positive off-ball behaviour is based on German Football Federation (DFB-Deutscher Fussball Bund) principles of play and tactics taught in their coaching course curriculum. Two of their principles of play related to off-ball behaviour are supported by previous research. These include exploiting space behind and provoking gaps within the opponent's defense (Memmert et al., 2017; A. Tenga et al., 2017). All actions including deep runs (DRs), synonymous with a straight sprint at near maximal velocity, and change of directions (CODs), characterised by a significant acceleration and/or deceleration combined with a turning or cutting movement, are two ways to achieve these outcomes. Further, the ability to quickly execute these movements has been shown to distinguish between standards of play and often precede goals scored (Faude et al., 2012; Carlos Lago-Peñas & Dellal, 2010).

These movements (DRs and CODs) that create a clear separation between the offensive and defensive player will be used to evaluate a novel *player pressure model* based on the existing pressure model (Andrienko et al., 2017) that accounts for the threat direction towards the goal. The evaluation of this method involves three steps. The first step used to validate the pressure model assumes that successful passes are completed more frequently to players under less pressure. Therefore, it is hypothesized that higher pressure on recipients is related to lower pass success. Secondly, it is hypothesized that off-ball behaviour consisting of DRs and CODs will correspond to decreases in defensive pressure demonstrating that the model can identify subtle changes in defensive pressure on off-ball players. Furthermore, it is expected that the time course will differ between DRs and CODs, but pressure will increase whenever the defender starts to adjust to the DR or COD and recover his defensive position. Finally, it is expected that decreases in defensive pressure during DRs and CODs will differ between positions and players in offensive positions (Strikers, Wide Midfielders, and Central Midfielders) will perform more off-ball actions than players in defensive positions (Central Defenders, and Wide Defenders).

5.3 Methods

5.3.1 Data Sample

The data for the present research was collected retrospectively from twenty-two official games of the German men's national team. Matches were played between 2013 and 2019 and included fourteen competitive matches, i.e., either World Cup or European Qualification games, or Nation's League games, and eight friendly matches. Match selection was limited due to the prevalence of time-based only, incompatible MTC (MIDI time code) event data files and PAM (portable arbitrary map) tracking data files that could not be utilised in the dataset. The sum of matches yielded 25,418 total passes accounted for by positional tracking data and 1229 movements off-ball that met the defined criteria for notational analysis presented below. Given the large number (N>1000) of both passes and off-ball actions in the data set, the sample size was justified with a power score of 1.0. The effect size is .3 with a margin of error of ± 5% with a lower critical N = 565 and upper critical N = 635.

Before analysis of the data, each match was pre-processed with ImoClient software (Inmotio Object Tracking B.V., The Netherlands) to synchronize both data streams and ensure a uniform data structure (Inmotio Object Tracking B.V., The Netherlands).

5.3.1.1 Notation of CODs and DRs

Notational analysis was used to identify timestamps of qualified DRs and CODs by three expert-observers (M.H, T.S., T.H.). All matches were viewed in Avidemux Software (cross platform, General Public License) which allowed for match time to be annotated the nearest tenth of a second. For DRs and CODs to be included in the study, they had to comply to several criteria based on previous literature discussed below and defined during the training-process.

Both CODs and DRs must have occurred in the opposing team's half in the pre-offensive and/or offensive zones when ball possession was established in the opponent's half in the pre-offensive, or offensive zones of the field (see Figure 6) (Bondia, González-Rodenas, Moreno, Pérez-Turpin, & Malavés, 2017). The movements were included in the analysis regardless of whether a pass was attempted to them or not.

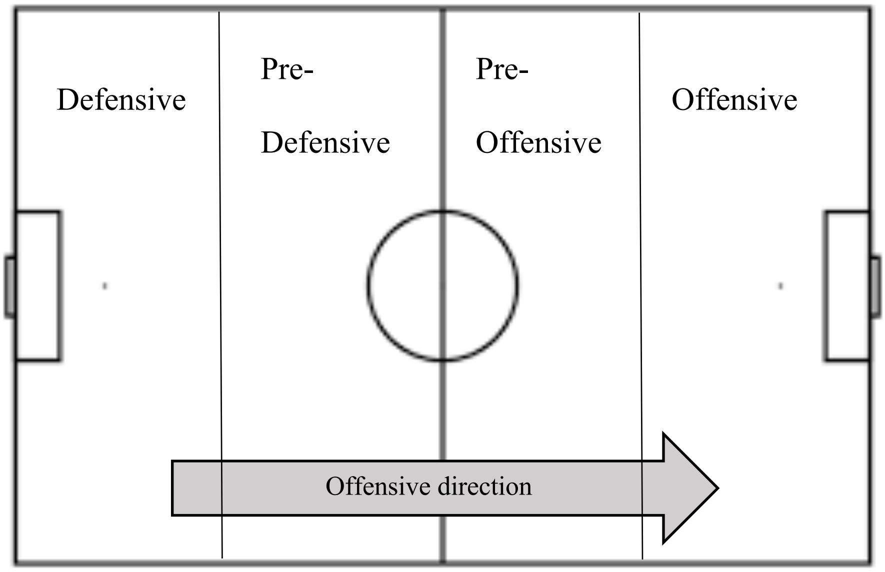


Figure 6: Zones of the field (Bondia et al., 2017)

5.3.1.1.1 Notation of DRs

Inclusion of DRs required at least 1s of sustained acceleration on the opponent's half (even if the run started in their half) that covered a minimum of 5 m from the start to the end of the time-window. If a change of direction (COD) of greater than or equal to 45 degrees occurred within the time-window, it was determined to be a COD and not a DR. If the offside line or opponent obstruction prevented them from meeting the criteria of the 1s of sustained acceleration, a DR was not achieved. The intention to make a DR was irrelevant in those cases. Lastly, based on an imaginary line running from one end line to the other, the aggregate (i.e., if the run was curvilinear) of the angle to that line created by the player's run must be less than 45 degrees. In other words, the player should ultimately be moving towards the opponent's end line as opposed to moving towards the sidelines or towards their own goal. The DRs were considered over when a player either received a pass, the player concluded their run in an offside position before the ball carrier played a pass (thus making him ineligible to receive the ball), the ball went out of bounds, or the player significantly decelerated.

5.3.1.1.2 Notation of CODs

A COD can be defined as the ability to decelerate, reverse or change movement direction, and accelerate again (Brughelli, Cronin, Levin, & Chaouachi, 2008). For inclusion, the action had to be an active movement and not a reaction to a teammate or deflection of the ball. As established in previous studies, CODs are characterized by directional changes ranging from 30°-180° (Jeffrey B Taylor, Wright, Dischiavi, Townsend, & Marmon, 2017), with a reduction in velocity while approaching the change of direction and increasing exit velocities (Dos'Santos, Thomas, Comfort, & Jones, 2018; Schreurs, Benjaminse, & Lemmink, 2017). Thus, in this study, CODs must have consisted of an angle greater than or equal to 45 degrees with a visible "cutting" action demonstrating substantial deceleration and/or considerable acceleration occurring within a .5 second timeframe. There were three possible situations in which a COD would be included. First, the player could use a sudden strong acceleration combined with a countermovement to trick the defender into going a different direction. Second, the player could suddenly stop, creating a high deceleration and minor acceleration to create space between him and the covering defender. The third option combines the two above mentioned actions where the player could have a high deceleration and acceleration in his COD to free himself from a marking defender. Significant deceleration and acceleration were defined to have a minimum of -2,5 m/s^2 and 3 m/s^2, respectively (Akenhead, Hayes, Thompson, & French, 2013). The CODs were considered over when a player either received a pass, the player concluded their run in an offside position before the ball carrier played a pass (thus making him ineligible to receive the ball), the ball went out of bounds, or the player significantly decelerated.

5.4 Ethical Considerations

The data was previously collected for performance purposes and not collected for experimental purposes. All involved players are professional players who provided consent to their national teams to collect, share, and store their data. Written informed consent was provided for the use of the data, and the study fully complies with the guidelines stated in the Declaration of Helsinki (2013).

5.5 Reliability Testing

Notational analysis was performed by three expert observers who each watched two-thirds of the games to ensure all games were examined by at least two experts. All inconsistently rated moments were later reviewed by the third observer for the final verdict. The use of expert observers to identify different match actions through notational analysis has shown a high level of inter-operator reliability (Liu, Hopkins, Gómez, & Molinuevo, 2013). To assure the quality of the notation analysis the experts went through a two-week training procedure annotating five different games and discussing their agreement afterward. The quality of the interrater reliability was measured in Fleiss Kappa, which is validated for inter-rater reliability testing in notational analysis of multiple sports including football (Fleiss, 1971). For the notational analysis, a Fleiss Kappa of .80 for DRs and .78 for CODs and was achieved.

5.5.1 Off-Ball Pressure Indicator

Pre-processing consisted of filtering the data with a weighted Gaussian algorithm (85% sensitivity) and automatic detection of ball possessions and ball events based on synchronization of the tracking data and manually tagged event data. All data were mapped to the same standard field size (105m x 68m) where the X-axis runs longitudinally from goal to goal (-52.5m to +52.5m), and the Y-axis runs horizontally along the midline (-34m + 34m). After pre-processing, position and event data were exported to a *. JSON format and all further processing, analysis, and visualization were conducted using custom routines packages programmed in Python 3.7.

The model of the off-ball pressure indicator (OBPI) consists of an oval shape field around the player making the DR or COD, also considered the pressure target. The pressure value (Pr) is calculated through Equation 1, in which d is the distance between the off-ball player and a covering defender and L forms the distance limits for the oval-shaped pressure field. The distance threshold L is dependent on the distance from the center of the goal, linearly decreasing by 5% every 5-meter distance to the goal, with a sharp increase when entering the penalty-box. The constant q is to regulate the speed at which the pressure value changes due to an increasing distance value. The most fitting value for q was earlier determined to be 1.75 (Andrienko et al., 2017).

$$\mathrm{Pr} = (1 - d/L)^{q} \times 100\% \tag{1}$$

The distance limits value (L) is constructed through Equation 2. D_back and D_front represent the distance limit for the pressure coming from behind and in front of the pressure target, respectively. These back and front limits have been determined to be respectively 3 m and 9 m based on the original model by Andrienko et al., 2017, who established these values by consulting football experts of the German Football Federation and presented them the results of different threshold values (Andrienko et al., 2017). However, in an additional workshop with coaches and match analysts of the German Football Federation and the current authors, it was determined that a fixed value of 9m as chosen by Andrienko et al. (2017) does not present pressure correctly during situations in close proximity to the goal. To correct for this, the front limit was set as dependent on the distance to the goal of the attacker as described in Equation 4. Now in situations closer to the goal, where pressure where pressure would normally start a 9m, pressure is registered at closer distances that are more realistic

The z-value is calculated through Equation 3, where Θ is the angle between the direction of the target and the direction of the pressure exerted by the covering defender.

$$L = D_{back} + (D_{front} - D_{back})\,(z^3 + 0.3z) / 1.3 \quad (2)$$

$$z = (1 - \cos\Theta)/2) \quad (3)$$

$$D_{front} = 9 - 0.05\,(105 - \text{GoalDist}) \quad (4)$$

These equations create an oval shape that represent the pressure field in which an attacker can be pressured by opposing defenders. A visualization of the pressure model (see Figure 7) shows opposing defenders who enter the oval around the pressure target and exert pressure on the off-ball player, while the threat direction is the direction towards the midpoint of the goal. The maximum theoretical pressure exerted on the target player is 100%, occurring when a defender is immediately in front of the target player on the threat direction line. The value of Pr is between 0 (no pressure) and 1.0, representing 100% (maximum theoretically possible) pressure. Several pressers Pi can simultaneously exert pressure on the same target T. This way, the model gives real-time quantification of the exerted pressure of a single defender or multiple defenders by taking the sum of their pressures. Thus, the total pressure on a target can exceed 100% and give values over 1.0.

The model originally assigned attacking players in an offsides position a pressure value of +1, or the addition of 100% pressure. However, after analyzing the data it was discovered that the offside detection needed to be removed since it led to abrupt pressure changes in the time-series and a player with 100% pressure can still theoretically receive a pass while a player in an offsides position cannot. All off-ball actions that took place entirely in an offsides position were removed from the data set and if there was a change in pressure greater than 70% within 0.1 seconds, after confirmation via video inspection, 1 was subtracted from the reported pressure value to remove the false addition occurring from the offsides. Therefore, the model should create an opportunity to discover the pressure quantities exerted throughout moments of significant off-ball behaviour by the pressure target.

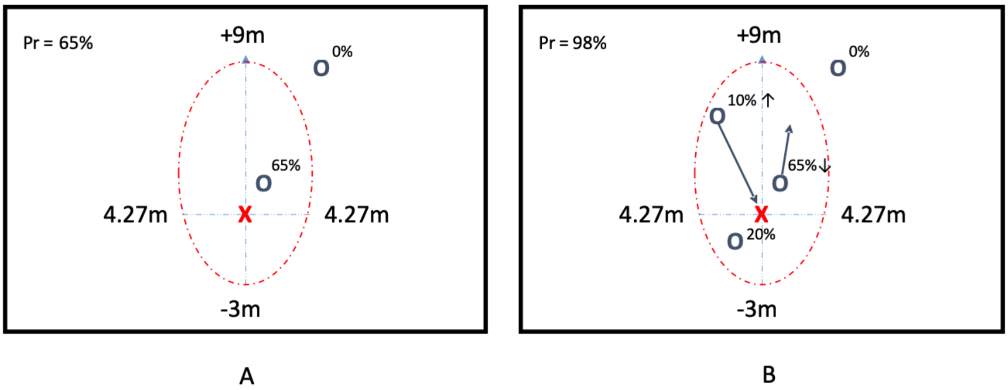
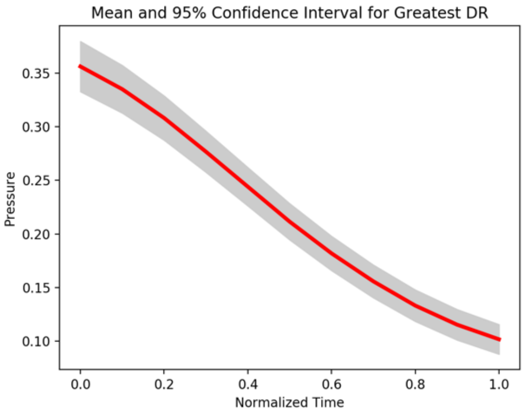


Figure 7: Visual representation of the pressure (Pr) zone. Red X represents the attacking player while the O's represent defenders. A) An example without relative movement with one defender in the pressure zone applying 65% pressure. B) Considering distance of decay (q) moderated by relative movement yielding 98% pressure.

5.5.2 Individual Off-Ball Behaviour Analysis

Defensive pressure is calculated for each player for every 0.1 seconds of a second frame. Off-ball movements such as a sprint or a rapid change of direction can lead to a decrease in pressure. This is illustrated below showing change in pressure from the raw data for DRs (see Figure 8) in Germany versus England match played November 19, 2013, and for CODs (see Figure 9) in Germany versus Netherlands match played on October 13, 2018.



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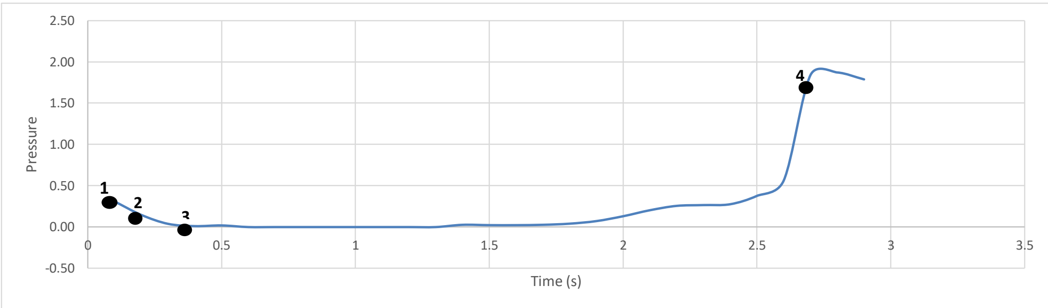
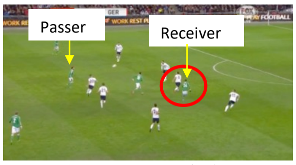




1. Start Pressure (.31)

Green attacker near the defender in white

2. Sprint Action (.15)

The attacker accelerates into a deep run to exploit the space behind the defensive line

3. Minimal Pressure (.00)

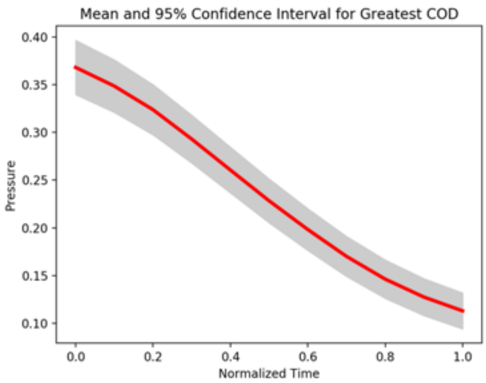
The deep run creates space away from the nearby defender before the goalkeeper can react to come off his line, achieving a minimal pressure value

4. End Pressure (1.73)

The goalkeeper comes out increasing pressure while the defender starts to recover to add some back pressure as the attacker tries his shot on goal

Figure 8: Change in pressure during a DR. A. All DR actions: normalised from 0 to 100% (x-axis), with a mean pressure line from start to finish, accompanied with shaded regions of variability showing 95% confidence intervals. B. Example showing how space is created with a decrease in pressure during a deep run for the offensive team (green jerseys) versus the defending team (white jerseys).

A



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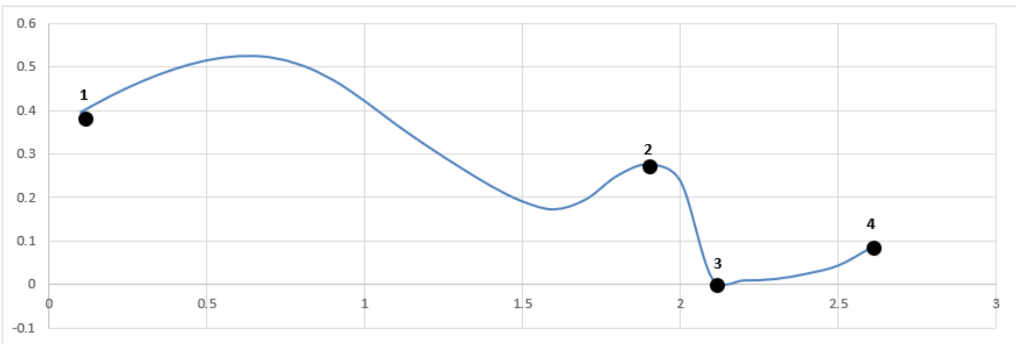
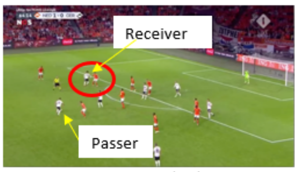




1. Start Pressure (.40)

The defender (orange jersey) near the attacker (white jersey)

2. Change of Direction Moment (.27)

The attacker starts a backpedal perpendicular to the goal direction and then cuts into a diagonal sprint towards the goal

3. Minimum Pressure (.02)

The change of direction creates space nearby defender, achieving a minimal pressure value

4. End Pressure (.08)

A second defender starts to cover for his beaten teammate and close down in the threat direction of the goal slightly decreasing increasing pressure on the attacker as he prepares to take a shot on goal.

Figure 9: Change in pressure during a COD. A. All DR actions, normalised from 0 to 100% (x-axis), with a mean pressure line from start to finish, accompanied with shaded regions of variability showing 95% confidence intervals. B. Example showing how space is created with a decrease in pressure during a deep run for the offensive team (green jerseys) versus the defending team (white jerseys).

5.6 Data Analysis

To test the plausibility the OBPI and evaluate the effectiveness of DRs and CODs, various statistics were implemented. In a first step, a frequency table was constructed for the friendly and competitive matches and analysed with a Mann-Whitney U test (SPSS Version 25.0) to ensure friendly and competitive matches would not show substantial differences between number of off-ball actions. There was no significant difference in the number of off-ball actions between competitive matches (Mean Rank 594.17) and friendly matches (Mean Rank 573.95) with $z = -1.209$, $p = .227$. Given these results, friendly and competitive matches were combined in the analysis.

In the next step, to investigate the validity of the OBPI, the association with pass completion was tested. Assuming decreased pressure would be related to an increased chance of pass completion, the reception and interception of all passes ending in the opposing half were identified and labelled. Next, the potential receivers for every pass were identified and the pressure on the potential receivers (not the passer) was computed at the moment the pass was made. To examine the correlation between pressure and pass completion, a Point Biserial Correlation Analysis was used in SPSS Version 25.0.

To further evaluate the OBPI, a time series analyses on the annotated movements (DRs & CODs) was conducted. The global trend analysis was calculated for the start to finish for each movement. The range for DRs Range was between 0.2 - 2.8 seconds and the range for CODs was between 0.2 - 2.6 seconds. For the local trend, change points were used to determine when pressure either increased or decreased by splitting the time series into two or more segments (Priyadarshana & Sofronov, 2014). Change points can occur in the time series characteristic of any field of science (Aminikhanghahi & Cook, 2017) and are considered as boundaries between two adjacent segments of data separated by quasi-constant differences (features that have the same values for a very large subset of the outputs, or shifts), a change in trend, and by changes in the variance of data (Topál, Matyasovszkyt, Kern, & Hatvani, 2016). In this study, intervals of sustained decreases in pressure measured in time steps of 0.1 seconds were identified for each movement by finding local maximums and local minimums. These intervals were then categorized into the longest sustained decrease without a plateau, the greatest decrease measured in pressure, and the fastest rate of decrease measured in pressure/second. The data from the local trend analysis was only moderately skewed via visual inspection of a histogram.

To determine differences in off-ball pressure changes between DRs and CODs, a mixed linear model was conducted, calculated at ninety-five percent confidence intervals. Run type (DR or COD) was included as the fixed effect with the local maximum as a fixed effect on a continuous scale, whilst the players' position was the random effect (See Appendix A for the algorithm). Individual players who did not perform both a COD and DR were removed from the linear mixed model, reducing the number of players involved by 56% (from 164 to 72) and the number of off-ball actions by 14% (from 1411 to 1209). Processing and analysis were conducted using custom routines (pandas, NumPy, and Matplotlib) programmed in Python 3.7.5.

The exact tactical formation for each team in the data set was unknown. As varying tactical formations have different numbers of players in certain positions (e.g. a 4-3-3 formation has two wingers for every one striker), playing positions were not normalized. A Mann-Whitney U test (SPSS Version 25.0) was utilized to determine if there were significant differences in runs between offensive and defensive positions.
An α-level of $P \leq 0.05$ indicated significance. For the mixed effects models, effect sizes (*d*) were determined as effect size with 0.2 be considered a 'small' effect size, 0.5 being a 'medium' effect size, and 0.8 being a 'large' effect. For Mann-Whitney U tests, effect size of $r < 0.3$ represents a small effect, between 0.3 and 0.5 being a medium effect, and greater than 0.5 being a large effect.

5.7 Results

5.7.1 Validation of Pressure Model Based on Total Pass Completion Rate

The sample for total passes was 25,418 passes, with 19,337 (76%) successful passes and 6,081 (24%) unsuccessful passes. The mean pressure on the pass receiver was .08 ± .40 for successful passes and .30 ± .22 for unsuccessful passes. Point Biserial Correlation Analysis for the difference in pressure on the pass receiver for passes completed vs intercepted revealed R= -.34 with a significance level of $p < .001$ (See Figure 13 in Supplementary Material). This indicates that receivers of successful passes had less defensive pressure at the moment of the pass.

5.7.2 Off-Ball Behaviour Results Overview

The total number of actions was 1411 with 988 (70%) DRs and 423 (30%) CODs. 252 of the annotated actions had no pressure during the entire action which indicates that no defenders entered the pressure oval at any time. For all actions, the average global trend was .02 ± .11 with a median of 0 and an IQR of .05. For DRs, the average global trend was .02 ± .10. with a median of 0 and an IQR of .04, and for CODs the average global trend was .02 ± .11 with a median of 0 and an IQR of .05.

For local changes, as seen in Table 6, the maximum pressure was greater for CODs than DRs. The longest decrease in pressure as well as the greatest decrease in pressure were also greater for CODs than DRs. Finally, the rate of decrease in pressure was faster for CODs than DRs.

Table 6: Pressure Values for an off the ball player performing a Deep Runs or Changes of Direction

	Overall	Deep Runs	Changes of Direction
	Mean ± SD	Mean ± SD	Mean ± SD
Maximum Pressure	0.33 ± 0.30	0.31 ± 0.30	0.37 ± 0.29
Longest Decrease in Time (seconds)	4.71 ± 4.59	4.53 ± 4.71	5.12 ± 4.26
Greatest Decrease (pressure)	0.20 ± 0.22	0.19 ± 0.23	0.21 ± 0.20
Fastest Rate of Decrease (pressure/time)	0.46 ± 0.59	0.42 ± 0.60	0.54 ± 0.55

5.7.3 Linear Mixed Model

The linear mixed model using run type (DR or COD) as a fixed effect with the local maximum as a fixed effect on a continuous scale resulted in $p < 0.001$, $d = 4.81$, CI = 0.63 to 0.67 for the greatest decrease, $p < 0.001$, $d = 0.143$, CI = 9.18 to 10.61 for length of the longest decrease, and $p < 0.001$, $d = 1.13$, CI = 0.90 to 1.11 for the fastest rate of decrease. There was no significant difference between DRs and CODs for greatest ($p = .435$, $d = -0.0478$, CI = -0.02 to 0.01) and longest ($p = .374$, $d = 0.054$, CI = 0.02 to 1.11), although fastest rate of decrease had a slightly stronger but still small effect with $p = 0.054$, $d = 0.118$, CI = 0.03 to 0.17. These results demonstrate that higher pressure at the start of the action is associated with decreases in pressure of higher magnitude with large effects, duration of decrease with small effects, and rate of decrease with large effects.

Table 7: Difference in pressure changes between run types: Fixed Effects (DR versus COD) with Local Maximum as the Covariate and Random Effects

	Fixed effects		**Random effect**
Outcome variable	p COD_DR	p Covar (local maximum)	Percent of total Variance explained by Individual Player Identity
Greatest Decrease	0.435	<0.001	3
Length of Longest Decrease	0.374	<0.001	<1
Fastest Rate of Decrease	0.054	<0.001	1

The average number of off-ball actions per player was 16.8 ± 26.2, median 7, and IQR of 10. As seen in Table 8, DRs are more common than CODs and wide midfielders performed more off-ball actions, especially DRs, compared to other positions on the field. The Mann-Whitney U test revealed that offensive players (CM, WM, ST) completed significantly more actions than defensive players ($p < .0001$) with a medium effect size ($r = .44$).

Table 8: Off-ball actions by position

Position	**DRs**	**CODs**	**TOTAL**
Central Defenders	6	2	8
Wide Defenders	82	19	101
Central Midfielders	162	65	227
Wide Midfielders (includes wingers and wingbacks)	365	184	549
Strikers	184	140	324

Although the model shows a clear effect of the local maximum for longest decrease, greatest decrease, and fastest rate of decrease in pressure, as seen in Figures 10-12, aside from some outliers there was not a significant difference between changes in pressure for different playing positions. However, there is a noticeable correlation between the start pressure of the local maximum (x-axis) and each metric (greatest decrease, longest decrease, and fastest decrease) (y-axis) as the plots follow this positive slope. The isolines (z-values), similar to elevation contour lines, represent the density of points. There is no defined progressive increment between successive contour lines, they are used as a relative visualization tool.

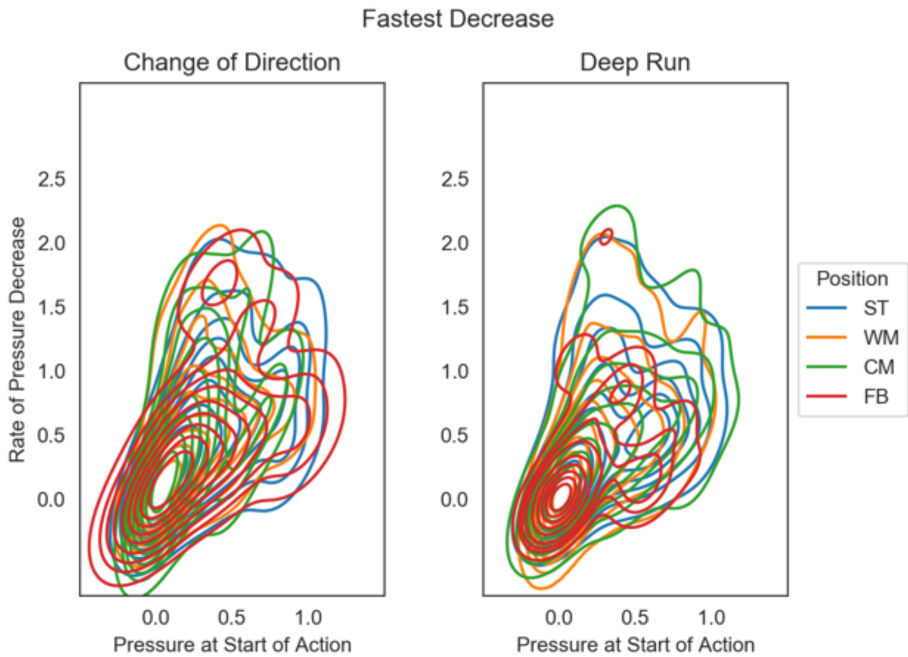


Figure 10: Fastest decrease in pressure between positions for DRs and CODs from the local maximum.

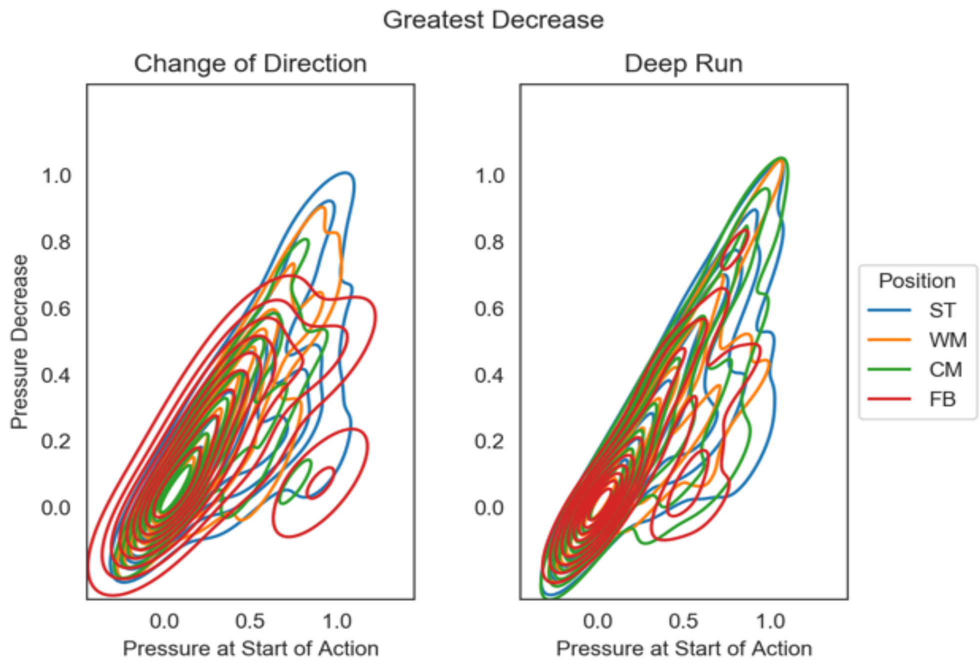


Figure 11: Greatest decrease in pressure between positions for DRs and CODs from the local maximum.

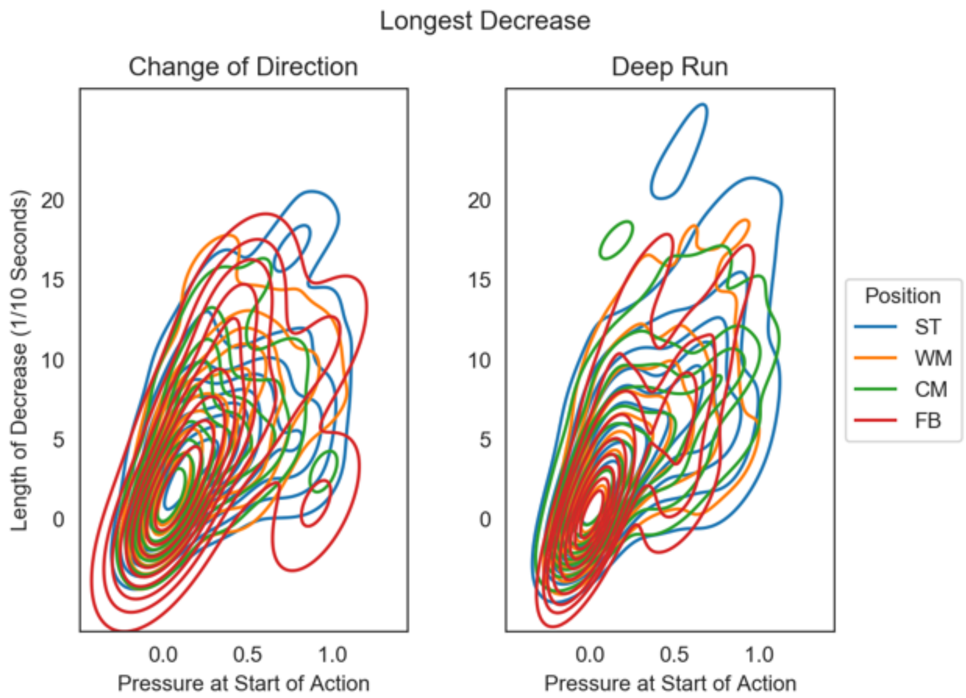


Figure 12: Longest decrease in pressure between positions for DRs and CODs from the local maximum

5.8 Discussion

The current research aimed to demonstrate the application of an adapted pressure model for the quantification and visualization of defensive pressure exerted on attacking players without ball possession. Expanding on earlier work on pressure (Andrienko et al., 2017), the presented model was implemented to analyze multiple games consisting of hundreds of closely examined match events. The approach of combining notational analysis with data science on a large sample size increases the effectiveness of the data analysis by notating and examining match events before the data processing (Nic James, 2006). Whereas previous research on pressure (Link et al., 2016) was based on the position of the defender(s) concerning the ball carrier, the approach in this study considered pressure exerted on players without the ball.

5.8.1 Validation of the Pressure Model

The first step evaluated all passes using positional tracking data to examine the reliability of the pressure model. Results showed a significant, medium degree of correlation with pressure on the receiver at the time the pass was made. The completion rate (76%) differed only slightly to other work on evaluating pass completion (61.8%) based on the defensive context in a large sample size of passes (F. R. Goes et al., 2018). Generally, passing studies have only taken the position and movement of the passer and the receiver into account (Szczepański & Mchale, 2016). However, pass outcome involves the combination of multiple variables such as field location and position (e.g. high risk passes compared to passes with little to no pressure in the backfield) (O'Donoghue, 2004), the length of different passes (Rampinini et al., 2009), communication between players (Duarte, Araújo, Correia, & Davids, 2012), and technical performance and decision-making (Liu, Gómez, Gonçalves, & Sampaio, 2016). For example, attempting riskier passes with a higher chance of turnover carry greater reward in terms of creating goal-scoring chances (Power et al., 2017). Considering those variables, the results in this study - following the hypothesis - show that less pressure on the receiver is associated to pass accuracy.

5.8.2 Changes in Pressure During DRs and CODs

It was hypothesized that off-ball behaviour consisting of DRs and CODs would correspond to decreases in defensive pressure, demonstrating that the model can identify subtle changes in defensive pressure on off-ball players. The adapted pressure model worked as intended, detecting an expected change in pressure exerted on the player performing a DR or COD. As evident in Figures 8 and 9, compared to the start of the action, the pressure typically decreased towards a minimum point which reflects the window of time the offensive player creates separation from the covering defender. On average, greater maximum pressures created the potential for a greater decrease, longer decrease, and a faster decrease in pressure. If the starting pressure was high, offensive players managed to create more space as defenders could not react properly to the off-ball movement. This trend was greater for CODs than DRs which could be due to the inherent nature of CODs in which the offensive player will travel in one direction, drawing the defender towards him before quickly cutting and moving in another direction (Davids et al., 2012). Clever attackers use the defenders' delay in perception-action coupling to take advantage of the defender's response to a fake or change of direction (Young & Murray, 2017). In addition, attackers may use different actions in specific situations. DRs are more of a space exploitation strategy to get behind the defense versus CODs which are more often used as a strategy for space creation.

Although DRs do not involve intentional misdirection like CODs, they too involve the closing of distance between the attacker and defender followed by a subsequent decrease in pressure. This pressure pattern was apparent in the time-series results and visualized in the notational analysis process when an attacking player attempted to run past a defender to exploit the space behind him; the space between the two players closed before it became a foot race to the ball. Similarly, when the distance between the attacker-defender dyad decreased in 1 versus 1 situations, there was an increase in both players' speed, especially the attacker's speed who is attempting to create separation to take a shot on goal (F. M. Clemente, Couceiro, Martins, Dias, & Mendes, 2013).

Due to the importance of sprinting performance in football, physical speed is a coveted quality which distinguishes players from the top leagues in Europe to other ones (Haugen, Tønnessen, Hisdal, & Seiler, 2014). A faster moving attacker in comparison to the nearby defender has the advantage when it comes to the creation of dangerous space (Fernandez & Bornn, 2018). However, as demonstrated by the effectiveness of CODs (misdirection) on decreases in pressure in this study, there are factors beyond sprinting ability that are important in creating differences in relative velocity. Such strategies include the use of positioning and the element of surprise that can provide the attacker an advantage, even when facing a faster defender. For example, movement into the defender's blind spot or between two defenders (causing confusion on which defender should be responsible for tracking the attacking player's movement) may provide the attacker with a head start. Perhaps the higher work rate preceding successful goal scoring opportunities discovered by Schulze et. al (2021) elicits fatigue in defenders which not only impairs their motivation to intercept passes (Barte, Nieuwenhuys, Geurts, & Kompier, 2020), but decreases their ability to perform sprints needed to prevent penetrating passes (Passos, Amaro E Silva, Gomez-Jordana, & Davids, 2020).

Finally, was expected the pressure would increase whenever the defender starts to adjust to the DR or COD and recover his defensive position. A slight increase in pressure (.02 ± .11) was found for the start to finish, or the global trend of every off-ball action. Whilst offensive players exhibit greater freedom of movement to create space, a defender's focus is predominantly on maintaining proximity to their opponents (Moura, Santana, Vieira, Santiago, & Cunha, 2015). As seen in Figures 8 and 9, the pressure value often increased from the minimum pressure point to the end of the movement when the covering defender adjusted to the action made by the attacking player. This pattern was observed in other work studying attacker-defender dyads in 1v1 situations where the defender would recover his position after being overtaken by an attacking player on the dribble (F. M. Clemente, Couceiro, Martins, Dias, et al., 2013). The increase in pressure towards the end of the off-ball action can also be explained by instances when the intended pass was completed, the attacking player stopped their off-ball action when the intended pass was intercepted, or the ball was passed to another player on the team. In addition, offensive players often make runs into the crowded penalty box where there is usually a greater density of defensive players (P. Santos, Lago-Peñas, & García-García, 2017). Furthermore, the start and end of the off-ball actions were determined by notational analysis which showed many of the actions started with low or zero pressure values. This is normal when considering the prevalence of zonal defending where defenders do not stick to a man but defend what is considered valuable space (Frias & Duarte, 2014) – often central and behind them near their own goal.

5.8.3 Changes in Pressure for DRs and CODs Based on Position

Results showed that wide midfielders, including wingers typically found in a in a 4-3-3 variation formation and wingbacks in a 3-5-2 formation, followed by strikers, made the most total actions.
This is in line with other research showing high-intensity actions performed by the attacking team are made predominately by wide midfielders and strikers (Di Salvo et al., 2009). As wide players and strikers are players positioned closer to the opponents goal, the use of high-intensity actions is an effective strategy to penetrate the defense and increase the reward of passes in the opponent's half, especially around the penalty box (Power et al., 2017). These findings are also in line with Steiner et al. (2019) who discovered that increases and alterations in movement speed benefit pass reception. Interestingly, in this study there was no significant difference between playing positions and changes in pressure. Perhaps this is because only movements made in the attacking half of the field were measured in this study and it has been shown (Luís Vilar, Araújo, Davids, & Bar-Yam, 2013) that teams consistently use numerical superiority as a defensive strategy.

In general, the pressure pattern seen throughout the time-series demonstrates that DRs and CODs indeed fulfill an important role as offensive tools, as demonstrated in prior studies (Faude et al., 2012; Carlos Lago-Peñas & Dellal, 2010). Moreover, the OBPI visualizes these findings that can be underpinned with actual values showing that players off the ball use movements like DRs and CODs to create windows of separation. These findings give further support to the approach developed by Andrienko et al. for on-ball pressure and extend its use to evaluate off-ball pressure.

5.9 Limitations and Future Work

The present study was not without its limitations. In addition to the observational character of the study, data was extrapolated from one team and only tested plausibility hypotheses at the exclusion of experimental testing. Such lack is prevalent not only in the present work but other work in the field and is a factor that precludes more definite conclusions. Though the pressure model could determine when a player is getting more open than they were before via a decrease in pressure, no threshold in openness was determined. A threshold may not be possible as is not uncommon for teams to use a player-focused passing strategy, prioritizing passes to key players with higher levels of skill even when they are under greater defensive pressure (Gyarmati & Anguera, 2015). For instance, one popular strategy to gain territory includes playing forward passes that are not always played into areas of low defensive coverage, but to a target player who is holding off a defender on his back (Kempe et al., 2014).

Despite these limitations, the findings of this study are valuable because of the combined approach of event data with tracking data as well as the inclusion of many situations and passes. The model can also be useful to show that certain players maneuver themselves into open space in different zones of the pitch, even if they are not always rewarded with a quality pass (Spearman, 2018). Whereas physical trainers rely on GPS data to provide information about workload (Buchheit & Simpson, 2017), match analysts can use this model to inform practice about which players are creating (or allowing) space, and how it is occurring. Coaches can then design training exercises with constraints that encourage faster, more deceptive movement off the ball and provide objective, visual feedback. Perhaps the model can be combined with earlier work on attacking play that will expand existing knowledge on the synchronicity between passing and player movement off the ball (Gudmundsson & Horton, 2017; Link et al., 2016). These systems could be combined with work on passing patterns and the tactical role of different positions (Amatria et al., 2019; Gyarmati et al., 2014) which could lead to the development of a model to quantify and value decision-making in passing and build-up play as seen in basketball (Cervone et al., 2014). Future work evaluating off-ball behaviour using pressure should also consider not only the pressure on the pass receiver but pressure on the passer as well. This can include considering the initial position of the attacking player (regarding the central or lateral starting point) and the initial distance to the goal, as well as how the movement of certain attackers without the ball generates space for other attacking players (Fernandez & Bornn, 2018; L. Vilar et al., 2012).

5.10 Conclusion

In conclusion, the current study aimed to check the plausibility of an updated pressure model to quantify and visualize the pressure exerted on off-ball football/soccer players. Adaptations to the model presented by Andrienko et al., including changing the threat direction to the center of the goal instead of towards the goal line and the addition of a gradual decline in the pressure area closer to the goal, added additional practical validity. Results showed that less defensive pressure on the receiver of a pass correlated with higher pass completion rate and the use of DRs and CODs indeed lead to decreases in pressure, especially when the starting pressure is higher. Finally, offensive players, including wide midfielders and strikers perform more off-ball actions compared players in other positions. The findings demonstrate its usefulness for the real-time quantification of pressure and the difference between positions and various movement strategies. However, these adaptions should be further evaluated in additional studies. There is the potential for this model to be incorporated into existing models to create a comprehensive method for quantifying and evaluating broader aspects of offensive play.

Supplementary Material

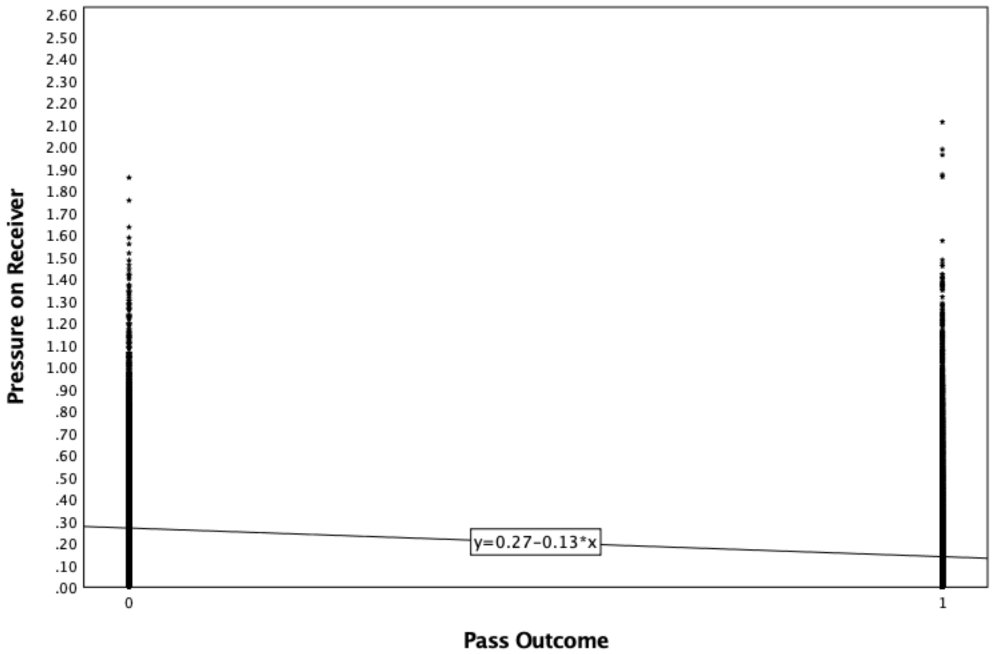


Figure 13: Pass OutcomeThis scatter plot visualizes that completed passes labeled as 1 on the x-axis had less pressure on the receiver at the moment of the pass than incomplete passes labeled as 0 on the x-axis.

Chapter 6: Shortcomings of applying data science to improve professional football performance: Takeaways from a pilot intervention study

This study has been accepted for publication following peer review. The content has been reformatted for this thesis. Full reference details for this study are:

HEROLD, M., KEMPE, M., RUF, L., GUEVARA, L. & MEYER, T. 2022. Shortcomings of applying data science to improve professional football performance: Takeaways from a pilot intervention study. Frontiers in Sports and Active Living, 4
https://doi.org/10.3389/fspor.2022.1019990

6.1 Abstract

Positional tracking data allows football practitioners to derive features that describe patterns of player behavior and quantify performance. Existing research using tracking data has mostly focused on what occurred on the pitch, such as the determinants of effective passing. There have yet to be studies attempting to use findings from data science to improve performance. Therefore, 24 professional players (mean age = 21.6 years, SD = 5.7) were divided into a control team and an intervention team which competed against each other in a pre-test match. Metrics were gathered via notational analysis (number of passes, penalty box entries, shots on goal), and positional tracking data including pass length, pass velocity, defensive disruption (D-Def), and the number of outplayed opponents (NOO). D-Def and NOO were used to extract video clips from the pre-test that were shown to the intervention team as a teaching tool for two weeks prior to the post-test match. No significant differences were found between the Intervention Team and the Control Team for D-Def ($F = 1.100$, $p = .308$, $\eta^2 = .058$) or NOO ($F = .347$, $p = .563$, $\eta^2 = .019$). However, the Intervention Team made greater numerical increases for number of passes, penalty box entries, and shots on goal in the post-test match. Despite a positive tendency from the intervention, results indicate the transfer of knowledge from data science to performance was lacking. Future studies should aim to include coaches' input and use the metrics to design training exercises that encourage the desired behavior.

Keywords: soccer, performance analysis, data science, coaching, passing behaviour

6.2 Introduction

To date, research on data science in football has primarily used observational designs to extract what occurred on the pitch, such as how teams interacted spatially (W. Frencken et al., 2011) or the risk and reward of passes (Power et al., 2017). Some experimental studies using data science have also been conducted that have produced findings applicable to the coaching process. For instance, discovering technical and physical differences between small-sided games (SSGs) and 11v11 match play (Dellal et al., 2012), tactical differences between common playing formations (Low, Rein, Schwab, & Memmert, 2022) and some drawbacks associated with high-pressing (Low, Rein, Raabe, Schwab, & Memmert, 2021). However, other than a few professional teams who publicly utilize positional data for in-house performance analysis, there is a paucity of research attempting to use positional tracking data to improve performance in competitive settings (Memmert et al., 2019). The disconnect between research and practice, especially the lack of approaches using metrics and tools developed from data science was shown by a recent survey (Mat Herold et al., 2021). In the survey, just twenty-two percent of 145 professional practitioners reported the use of such approaches in training with 35% of practitioners using KPIs for matches and only 19% using them for both training and matches. This leaves considerable room to investigate if and how data science can be applied in the training process to foster player education and development. Therefore, this pilot intervention study using professional football players is the very first attempt to close this gap.

Pilot studies are valuable in that they allow for reduced sample sizes and encourage participation in the applied setting, merging the path of researcher and practitioner (El-Kotob & Giangregorio, 2018; Malmqvist, Hellberg, Möllås, Rose, & Shevlin, 2019). Furthermore, pilot studies are more conducive to the rigorous, fast-paced environment within professional sports offering feasibility and a preview of methodological challenges for larger studies (Coutts, 2016) (Thompson, 2020). In this work, a lengthier intervention would have been desirable, especially considering that viewing tactical video (the nature of our intervention) has shown not to elicit mental fatigue nor impair subsequent physical and technical performance (Ciocca, Tessitore, Mandorino, & Tschan, 2022). In addition, more subjects and subsequent passes would have served to power the study and improve test-retest reliability. However, difficulty in recruitment and logistical constraints justify the sample size for this pilot study (Hertzog, 2008). Factoring in the normal team video sessions, players' pre-training routines, post-training individual meetings, weight training, etc., it was determined by the coaching staff that anything more would interfere with the team's objectives.

Earlier studies using positional tracking have mostly involved the examination of passing behavior. This focus is warranted (and feasible) as passing is the most frequent individual tactical action in a game (F. Goes, Schwarz, Elferink-Gemser, Lemmink, & Brink, 2021) and therefore considered a key skill (Bush, Barnes, Archer, Hogg, & Bradley, 2015; Szczepański & Mchale, 2016). As such, we chose to focus on the improvement of passing effectiveness in this pilot intervention.

Studies using positional tracking data demonstrated effective passes force defenders out of position, creating space that leads to higher probability goal-scoring chances (Rein et al., 2017; Steiner et al., 2019). Perhaps this explains why winning teams have been shown to outplay more opponents with passes than losing teams (Memmert et al., 2017; Rein et al., 2017). In other words, passes that eliminate a greater number of defensive players increase the attacker's space control in front of the goal and can be ranked as effective (Rein & Memmert, 2016a). These increases in spatial dominance and outplaying defenders with passes had a positive effect on the number of goals scored and the chances of winning a game. Following the presented results, we chose to use the number of outplayed defenders (NOO) as one of the metrics to evaluate passing performance in this study.

Along with passes that outplay opponents in a vertical direction, sideways and backwards passes can force the defense to shift, leaving gaps between defenders. Considering the importance of unbalancing the defense, Goes et al. (2018) calculated a defensive disruptiveness score (D-Def: an aggregated variable to quantify passing solely based on tracking data) as an index that represents the change in defensive organisation resulting from a pass (F. R. Goes et al., 2018). The D-Def metric could distinguish top, average, and low performance passes by comparing D-Def, pass length, pass angle, and pass velocity in the top 10%, average 80% and bottom 10% passes ranked on D-Def score. Consistent with the findings of Chassy et al. (2013) (Chassy, 2013), the speed and precision of passes are predictors of success, corresponding to greater D-Def scores. Therefore, in addition to the number of outplayed opponents, D-Def was the second data driven metric used to measure the effectiveness of each pass.

One method utilized by most professional football teams to improve individual and team performance, including passing performance, is video analysis in the match planning and development of players (Groom et al., 2011; Wright et al., 2012). Video analysis offers coaches the opportunity to use pre-selected clips to assess performance and gives players the chance for critical self-appraisal (Brümmer, 2018). Reflective practice using video feedback has been demonstrated to be a useful tool to improve several cognitive components such as game understanding and decision-making in football (Groom & Cushion, 2005).

Despite being common in practice, research on video analysis in football has mostly covered practitioners' perceptions of video analysis (Reeves & Roberts, 2013) and how it is used in their daily work (Groom et al., 2011; Partington, Cushion, Cope, & Harvey, 2015). Therefore, further examination of the role of video feedback on performance outcomes would be a worthwhile purpose for research in football. Moreover, no studies have attempted to combine information gathered via positional tracking data and transform it into an educational tool to demonstrate effects beyond laboratory tasks, in real competitive situations. Therefore, this pilot study aims to examine the effectiveness of video feedback consisting of positive and negative examples of players' passes of two metrics - D-Def and number of outplayed opponents (NOO) - for the performance of individual and team passing performance. It is hypothesized that players on the intervention team will show significantly greater improvement in D-Def and NOO in the post-test match.

6.3 Methods

6.3.1 Participants

24 professional football players participated in this study (mean age = 21.6 years, SD = 5.7). All participants were rostered on a USL Championship team considered the United States 2nd Division in which they practice about eight to fifteen hours a week. The present research fully complies with the highest standard of ethics and participant protection which followed the guidelines stated in the Declaration of Helsinki (2013) and was approved by the ethics committee of Saarland University (registration number 2573003). All participants gave their written informed consent; parental consent was provided for players younger than 18 years of age.

6.3.2 Procedure

Pre and post-test matches consisting of 11v11 were played with each game lasting two fifteen-minute halves with a three-minute half-time period. Based on position, players were randomly selected to either control team or the experimental team. Both teams were evenly matched by coaches and were instructed to play in a 4-2-3-1 formation.

Following the pre-test match, the experimental team was shown video clips of six examples of passes with a low D-Def score (<mean) and six examples of passes with a high D-Def score (>mean) prior to joining the team for training sessions. The control team did not receive any intervention. During the video intervention session, each of the 12 passes was shown three times and the D-Def score as well as the Number of Outplayed Opponents were visible for players prior to and during each pass (See Figure 14). Thus, the Intervention Team viewed 216 passes in throughout the duration of the intervention with each intervention session lasting approximately 15 minutes in duration. During the video sessions and throughout the intervention, no coaching or feedback was given other than an initial explanation of how the D-Def metric and NOO metrics work and identifying each pass both orally and visually. Players were neither encouraged nor discouraged from discussing the video and/or their passes amongst themselves. The video played for 10 seconds prior to the execution of the pass and 10 seconds after the pass was completed to provide players with game context. This meant players could identify positive and negative behavior based on these numbers and the effect of each pass on their own. Showing both positive and negative examples was the chosen method as individual players respond differently to various forms of feedback (Groom & Cushion, 2005). At the conclusion of the intervention, the teams competed in an identical re-test and were evaluated again for their performance on the metrics. A placebo video was given consideration but since the professional players on the team involved have daily team video sessions lasting between 20-60 minutes it was deemed unnecessary.

Figure 14: Example of how players received video feedback for each pass on D-Def and Outplayed Opponents ("Pass Packing").

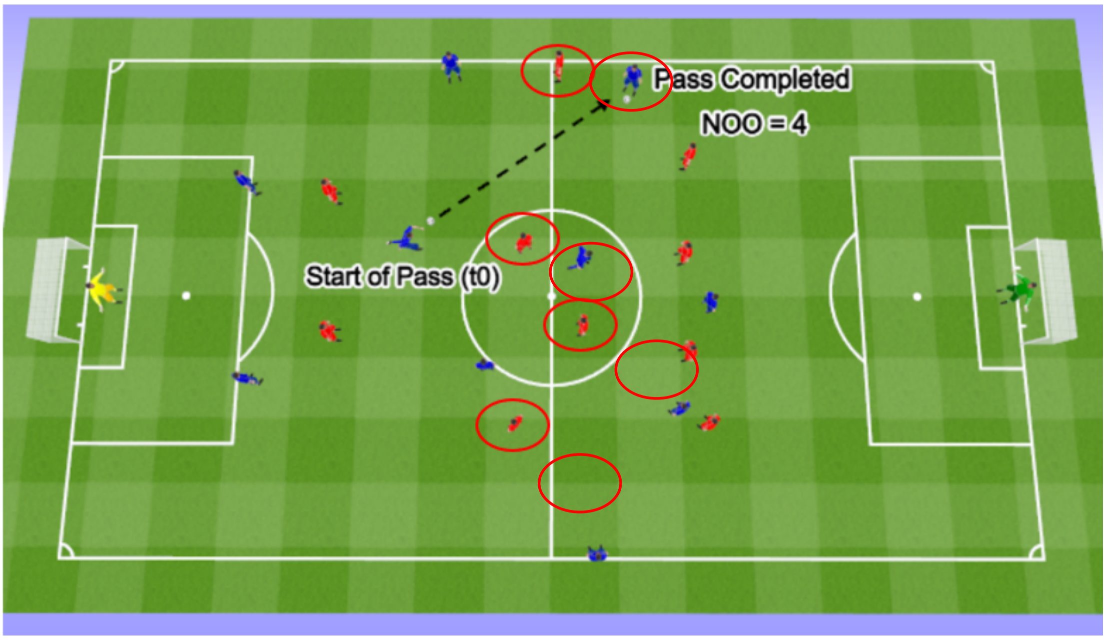
6.4 Data Collection

The pre and post-test matches were monitored and recorded via the camera at Segra Field in Leesburg, VA, provided by Spiideo (https://www.spiideo.com). To evaluate the performance of a team according to the tactical principles and analyse the relationship between tactical performance and match outcome and to assess the success of the chosen intervention (see below), positional tracking data was collected and processed. Players were tracked with a semi-automatic optical tracking system (STAT Sports; STATS LLC, Chigago, IL) that captures the X and Y coordinates of all players at 10 Hz. Every pass was tagged manually to the nearest 0.1 of a second for the moment the ball was passed to the moment the ball was received by an experienced match analyst. Both the tracking data and the ball event data were then imported as individual data frames in Python 3.6 and automatically processed on a match-by-match basis.

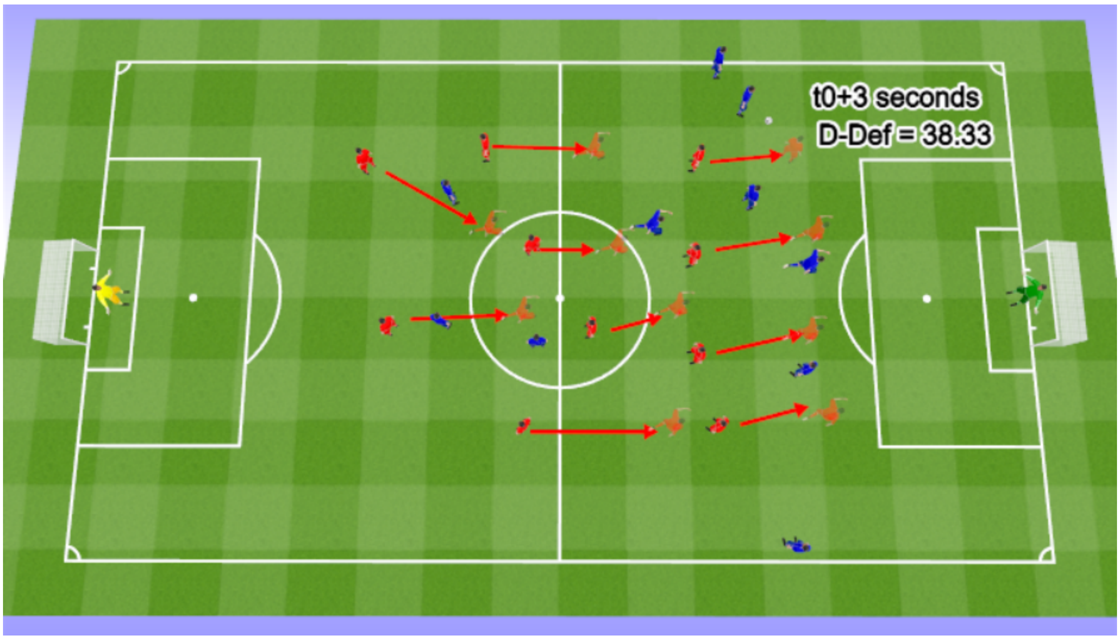
6.4.1 Metrics

D-Def - computed as the displacement of the average X and Y positions (or centroids) for the full team, and the defensive, midfield, and attacking lines between the moment a pass was given (t0) and 3 seconds later (t0+3). D-Def is constructed by three components: the disruption in the longitudinal and lateral directions, and disruption of the team surface and spread area (For an in-depth description, see (Leander Forcher, Kempe, Altmann, Forcher, & Woll, 2021). This results in a measure from 0 to 150 (with 0 indicating no disruption and 150 indicating a maximum of disruption).

Position data was also used to calculate the number of outplayed opponents (NOO) by determining the difference in opposing players between the ball carrier and target goal from the moment each pass is played to when it was received (Rein et al., 2017; Steiner et al., 2019). Therefore, NOO could range between -10 (10 more player between the original position and the goal) to 10 (10 less players between the original position and the goal).



A.



B.

Figure 15**.** A 2-dimensional representation of how D-Def and NOO were determined by a pass. The blue team is attacking towards the right against the defensive team in red. In Figure 15A, from the start of the pass (t0) to the time of pass completion, 4 defensive players (circled in red) were eliminated in the longitudinal direction. In Figure 15B, the red arrows represent the displacement of the defense from t0 to t+3 second, yielding a D-Def score of 38.33.

6.4.2 Statistical Analysis

Statistics for all passing-related performance metrics of the two teams were compared with one another for both the pre-test and the post-test matches. In the post-test match, four players (40%) from the control team and one player (10%) from the intervention team missed with one player out due to illness, two players got injured during the length of the intervention, and two players were called up to the 1st team. Therefore, after examining various approaches to handle missing data, we utilized a principled method by inputting a weighted nearest neighbors' approach in SPSS statistical software (Dong & Peng, 2013; Faisal & Tutz, 2021). D-Def and NOO are only applicable for completed passes and therefore, the sample comprised of 187 completed passes (95 pre-test and 92 post-test) in the control team and 184 total passes (76 pre-test, 107 post-test) for the intervention team.

Pre and post-test match team comparisons were made for the main dependent variables including D-Def and Number of Outplayed Opponents and descriptive analysis was completed for Number of Passes, Penalty Box Entries, Shots on Goal, Pass Length, and Pass Velocity.

Data for D-Def and Number of Outplayed Opponents were normally distributed for each factor combination based on a Shapiro-Wilk test. A 2x2 repeated measures ANOVA (timepoint×team) was used to test for interactions, main effects, and simple main effects for timepoint (pre- vs post-test matches) and team (Intervention Team vs Control Team) for D-Def and NOO with an alpha level of .05. Effect sizes were calculated using partial eta squared (η^2) with 0.14 or greater representing large effects, 0.06 or greater as medium effects, and 0.01 or more as small effects (Cohen). All statistical tests were carried out with the statistical software IBM SPSS Statistics Version 25. An a priori power analysis was conducted using G*Power version 3.1.9.7 (Faul, Erdfelder, Lang, & Buchner, 2007) to determine the minimum sample size required to test the study hypothesis. Results indicated the required sample size to achieve 80% power for detecting a medium effect, at a significance criterion of $\alpha = .05$, was $N = 96$ for a 2x2 repeated measures ANOVA. Thus, the obtained sample size of $N = 24$ players was low in statistical power. However, given the number of observations including 371 completed passes and the contextual and environmental constraints associated with high-performance sport, the sample size for this pilot study can be based on feasibility (Julious, 2005).

6.5 Results

A two-way ANOVA revealed that there was not a statistically significant interaction detected between the effects of timepoint (pre-test vs post-test) and team (Intervention Team vs Control Team) for D-Def ($F_{1, 31.73}$= 1.100, p = .308, η^2 = .058) or NOO ($F_{1, 18}$ = .347, p = .563, η^2 = .019). Similarly, there was neither an overall effect for the factor timepoint ($F_{1, 10.47}$= .363, p = .554, η^2 = .02 for D-Def; $F_{1, 18}$ = .128, p = .725, η^2 = .007 for NOO) nor for the factor team $F_{1, 18}$= 1.905, p = .184, η^2 = .096 for D-Def; $F_{1, 18}$ = .254, p = .620, η^2 = .014 for NOO). As seen in

Table 9, mean differences indicate that the Control Team's D-Def score decreased by 2.8, and their NOO score increased by .39. For the Intervention Team, their D-Def score increased by .76, but their NOO score decreased by an average of .09.

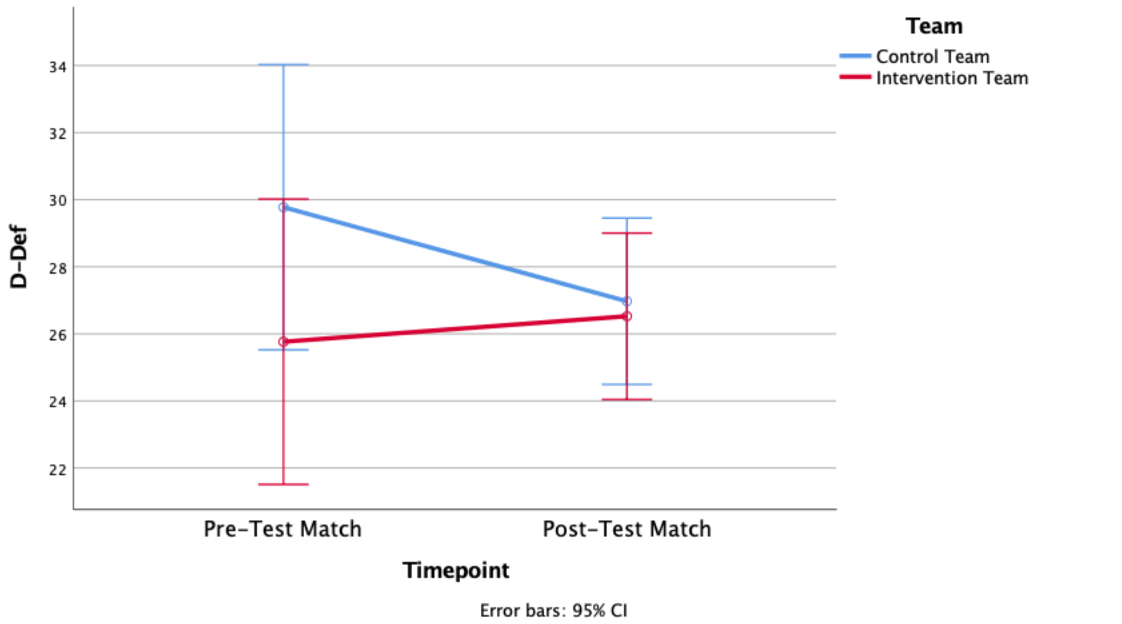


Figure 16: Differences in D-Def scores between Pre-and Post-Test matches for the Control Team and the Intervention Team.

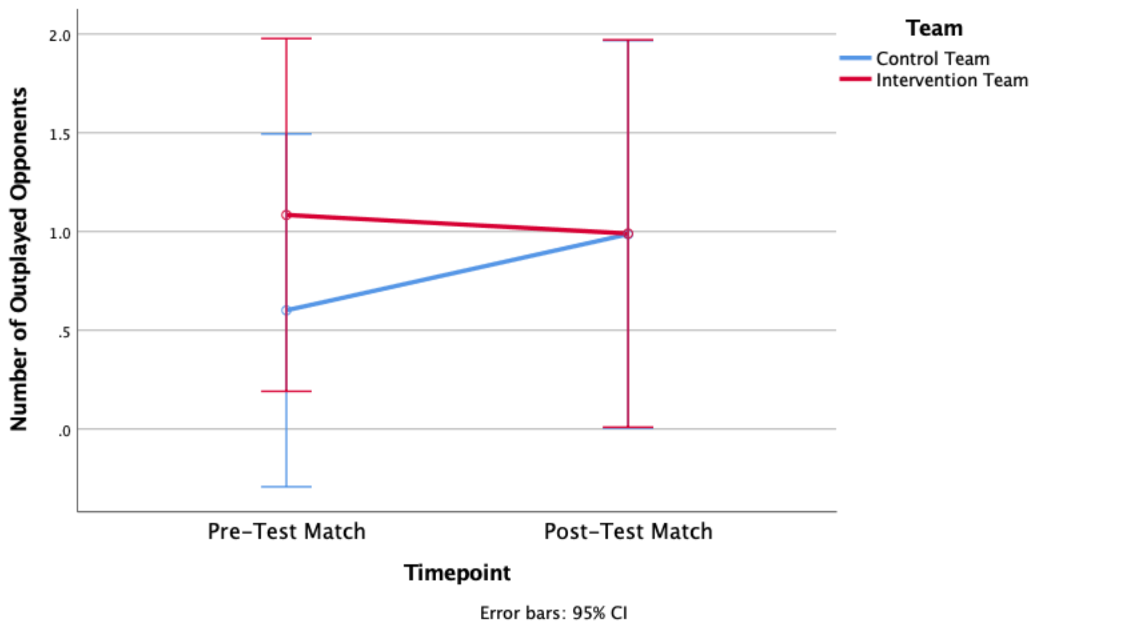


Figure 17: Differences in Number of Outplayed Opponents (NOO) between Pre-and Post-Test matches for the Control Team and the Intervention Team.

As seen in Table 9, the Intervention Team showed greater numerical increases for Number of Passes, Penalty Box Entries, Shots on Goal, and Pass Length. In contrast, the Control Team only made a slight increase in Pass Length.

Table 9: Team averages between pre-test and post-test matches

	Pre-test Control	Post-test Control	Pre-test Intervention	Post-test Intervention
D-Def	29.78 ± 6.46 95% CI = [25.52,34.03]	26.97 ± 4.28 95% CI = [24.49,29.45]	25.76 ± 6.34 95% CI = [21.51,30.02]	26.52 ± 3.1 95% CI = [24.04,29.00]
Number of Outplayed Opponents	0.6 ± 1.68 95% CI = [-.29,1.49]	.99 ± 1.57 95% CI = [.01,1.97]	1.08 ± .89 95% CI = [.19,1.97]	.99 ± 1.38 95% CI = [.01,1.97]
Number of passes	9.3 ± 6.63	7.4 ± 4.25	7.4 ± 4.38	10.3 ± 4.42
Penalty Box Entries	8	8	2	11
Shots on Goal	3	2	2	4
Average Pass Length (meters)	19.53±10.0	20.57±12.23	16.38±6.62	19.12±11.60
Average Pass Velocity (m/s)	12.4±4.53	11.98±4.13	10.97±3.47	10.96±4.35

6.6 Discussion

Disrupting the opponent's organization and outplaying opponents are important outcomes of effective passing. In theory, improving players' ability in these areas would increase their team's chances of scoring goals. Based on these assumptions, this study examined the use of a positional tracking, data driven video intervention in an experimental setting (11 vs. 11 football game) to investigate if well-established metrics of observational studies can be used to improve passing effectiveness.

In the present study, there were no significant differences found between the Control Team and the Intervention Team for either of the metrics gathered via positional tracking data: D-Def or Number of Outplayed Opponents. The improvements were only small, insignificant changes for D-Def (+.76) and a slight decrease in NOO (-0.09) for the Intervention team. Given that the control team's D-Def score decreased without any presumed external influence, the difference can be interpreted as a lower boundary for the reliability of the measurement procedure.

Despite no significant improvements for D-Def or NOO, the Intervention Team made greater numerical increases than the Control Team in more traditional key performance indicators (M. Herold, M. Kempe, P. Bauer, & T. Meyer, 2021), including Number of Passes, Penalty Box Entries, Pass Length, and Shots on Goal. Broadly speaking, the greater numerical increases shown by the Intervention Team supports previous studies that a video intervention can lead to general improvements in performance. These findings are supported by research in other sports showing improved decision making (tennis) and tactical knowledge (volleyball) with the use of video feedback
(García-González, Moreno, Gil, Moreno, & Villar, 2014; Moreno et al., 2016).

The Intervention Team's execution of more passes by players more frequently positioned in attacking areas of the field and gain seven extra Penalty Box Entries in the post-test match compared to the pre-test match is in accordance with previous studies finding passes from the midfield into the final third lead to greater penalty box possessions (J. Lago-Ballesteros, Lago-Penas, & Rey, 2012; A. Tenga, Holme, Ronglan, & Bahr, 2010a). This could be the result of the video intervention as D-Def and NOO show the highest values for these types of passes. Thus, the players of the intervention team might have prioritized these passes based on the information presented in the video clips. These results suggest in future studies it could be of interest to not only measure single passes, but sequences of passes to capture the combined effects of passes of different lengths, velocities, and vectors.

The failure to achieve significant improvement for D-Def and NOO could be due, in part, to low sample size, as well as limitations of transferability from the chosen form of video feedback to on-field performance. One aspect that may have limited the transfer to the field was the speed in which the video was played back. For example, video feedback on kicking performance and temporal patterns in U-10 players discovered only the slow-motion video group elicited significant improvements whilst the video played at normal speed did not (Quintana, Aguilera-Castells, Solana-Tramunt, Morales, & Nieto, 2019). Though in this study professional players were used, and the objective was to improve tactical performance more so than technical performance, use of slow-motion replay could have elicited greater improvements. Each pass was shown three times, but at normal playback speed the Intervention Team may have been unable to pick up on enough of the match context to determine what led to a specific pass having a higher or lower score.

Along the lines of decision making in football, one could argue that D-Def is too multifaceted and/or complex for players to consider in the chaos in a game. Although a player may comprehend that longer passes traveling at a greater velocity, in a slightly more forward direction cause the greatest disruption to the defense (F. R. Goes, Kempe, Meerhoff, & Lemmink, 2019), players must make rapid decisions relative to the match context. For instance, passing decisions are largely influenced by teammates' movement and positioning relative to the ball carrier as well as the organization of the defense; two factors which determine open passing lanes (S. Steiner, 2018). On the other hand, players in the Intervention group performed worse in the post-test match for NOO, a rather simple concept of subtraction. Further, well-known football terminology (and a popular metric called *Packing rate*) such as *breaking defensive lines,* and *penetrating passes*, exist, to illustrate the passing-related principle of play. Therefore, other limitations of the intervention must be considered.

One factor that could have limited transfer was the lacking coaches' involvement in the video education process. Thus, the onus was on the players' ability to reflect and their self-awareness, two prerequisites for learning (Larsen, Alfermann, & Christensen, 2012), to understand when they made good passes and/or how they could have made better passes. In this study, the feedback about each pass was quantitative as players were simply shown a number indicating the D-Def and NOO value of each pass. It is possible that a more qualitative assessment, such as a "debate-of-ideas" would have been more likely to pay dividends in performance on the field (Harvey & Gittins, 2014). Albeit the effectiveness of discussion in the video feedback process depends on a high level of trust between athletes and coaches (Nelson, Potrac, & Groom, 2014), the absence of open forum dialogue in this study could have limited decision making progress.

Besides more qualitative feedback from coaches, this study did not involve any exercises or drills on the field that could have enhanced player understanding and execution of the principles behind D-Def and NOO. Other intervention studies have involved specific training approaches with positive results. For example, a non-linear training approach (manipulating interacting constraints between the learner, task and environment) was found to improve decision making and actions (Práxedes, Del Villar Álvarez, Moreno, Gil-Arias, & Davids, 2019) and the integration of differential learning was found to enhance creative and tactical behavior (S. Santos et al., 2018). Ultimately, information derived by data science would not be limited to video analysis and ideally, it would stimulate discussions between match/performance analysts and coaches to find ways to improve training and match tactics. It is recommended that prospective research combines findings from data science into training exercises that underscore the perceptual-action relationships of the chosen metric/s. These studies could follow the lead of previous studies where researchers collaborated for multiple weeks with coaches to create the implemented training program (Harvey, Cushion, Wegis, & Massa-Gonzalez, 2010; Práxedes et al., 2019).

Finally, the length of the intervention process was also short in comparison to other studies. With the team involved being in the middle of their professional season, the intervention was only able to be applied for a total of six sessions due to logistics and the preference of the coaching staff. Previous studies showed the importance of including more than twelve sessions (Harvey et al., 2010; Pizarro, Domínguez, Serrano, García-González, & del Villar Álvarez, 2017) and increased results with more sessions (R. Araújo, Mesquita, Hastie, & Pereira, 2016). Thus, future work on the integration of data science to performance is advised to give attention to the length of education process.

In conclusion, this pilot intervention study made the first attempt to gain a better understanding about integrating spatiotemporal data to improve football performance. Positive and negative examples of passes based on quantitative measures led to marginal improvements in D-Def but a slight decrease in NOO. While there was no significant improvement in the passing metrics, the intervention team's performance improved based on more traditional key performance indicators. Thus, there was an indirect effect of the intervention, and it can be assumed that football players may benefit from video feedback when attempting to improve passing performance. We think, this first pilot study shows that metrics derived from data science could improve player performance and improve tactical training, if, like in this study, metrics are well explained to the players and data is processed quickly to facilitate the training. To continue bridging the gap between data science research and football practice, it is recommended future studies consider the length of the intervention, provide qualitative feedback, and include collaborative efforts between coaches and researchers to develop training sessions that reinforce any desired tactical behavior/s.

Chapter 7: General Discussion

This chapter provides a general discussion of the thesis, including a summary of the findings, major contributions to theory, methodology and practice, research strengths and limitations, and recommendations for future research.

7.1 Summary of Findings

In the following sections, a summary of the empirical studies is provided. This thesis presents several novel findings in relation to the use of data science in football. Table 10 summarizes each study's aims and main findings within this thesis. In general, the findings support the value of positional tracking data to give practitioners a deeper understanding of the attacking process. However, further evaluation of data science methods will be of central importance to confirm the efficacy of tactical parameters for professional football practitioners. This includes continually refining how to incorporate data-driven models to improve football performance.

Chapter 3 of the current thesis discovered what practitioners value, and gaps were identified in the literature for future work. A deeper understanding of what data-driven metrics are available to football practitioners is useful for monitoring developmental progress. In a similar review to Chapter 3, Thakkar et al. more recently reviewed several data science capabilities in football (Thakkar & Shah, 2021). These included the ability of network analysis to quantify the importance of a player and describe the interaction of team (Gama et al., 2014) and regression models to determine the probability of shots leading to goal (Fairchild, Pelechrinis, & Kokkodis, 2018). In agreement with Chapter 3, Thakkar et al. emphasized that demand remains to improve the collaboration between practitioners and researchers, including the overall handling of large amounts of data accompanying the advent of player tracking devices.

Player tracking technologies facilitated an increased availability of game data that can be used for practical and research purposes (Christopher Carling et al., 2008; Castellano et al., 2012). To optimise the effectiveness of data-driven approaches, it is important to understand the strengths and limitations associated with big data (Perl et al., 2013; Rein & Memmert, 2016a). Chapter 3 made significant progress in this area by presenting how machine learning methods are used and by sourcing the available literature on what has been done in football and what is needed in the future. The basic concept of machine learning with reference to tactical play in football was discussed, including using granular metrics to objectively quantify performance. For instance, literature on team centroids, or the average centre factoring all players on the field, revealed that there is often strong inter-centroid (between teams) coupling during match play and variability in inter-centroid coupling during key events like shots on goal (Duarte, Araújo, Davids, et al., 2012; W. Frencken et al., 2012).

Another area of focus on team tactics is the control of space. Two ways to determine space control include a convex hull which encloses all players from one team and Voronoi diagrams. As outlined in Chapters 3 and 4, both approaches can provide information such as how being in or out of possession impacts the amount of distance covered or how the ball's location on the pitch determines the density of players (Fradua et al., 2013; Moura et al., 2013; Taki & Hasegawa, 2000). Nonetheless, Chapters 3 and 4 further support the notion pointed out by Rein et al., (Rein & Memmert, 2016a) and Thakkar et al., (Thakkar & Shah, 2021), that a theoretical model integrating the physical, technical, and tactical aspects of the play is absent. Thus, the ability of practitioners to implement the analytical models remains a challenge (Christopher Carling et al., 2008; Nevill, Atkinson, & Hughes, 2008)

Table 10. Summary of Study Aims and Findings

Thesis Chapter	Study title	Aims	Findings
Chapter 3	Machine learning in men's professional football: Current applications and future directions for improving attacking play.	To gain a direction for future research by reviewing extant research that uses machine learning approaches to examine attacking football performance.	-Machine learning is a new field in relation to football, and the limitations of its use remain unknown. - Previous studies have focused extensively on passing performance and prediction. Gaps remain, such as the study of off-ball behaviour and a need for greater collaborative efforts between data scientists and practitioners.
Chapter 4	Attacking Key Performance Indicators in Soccer: Current Practice and Perceptions from the Elite to Youth Academy Level	Aim 1: To understand how coaches, analysts, and scouts use and value existing key performance indicators (KPIs) Aim 2: To understand practitioners' awareness and use of data-driven metrics	- Practitioners prioritize traditional KPIs gathered via notational analysis. - Practitioners are either unaware or do not have the resources to implement data-driven metrics into their practice.
Chapter 5	Off-Ball Behaviour in Association Football: A Data-Driven Model to Measure Changes in Individual Defensive Pressure	Aim 1: To implement an off-ball pressure model to capture changes in individual defensive pressure during deep runs (DR) and changes of directions (COD) Aim 2: To understand how positional differences influence the use of off-ball behavaiors and their subsequent change in defensive pressure	-There is a higher pass completion rate for players when a pass is played to a teammate with less defensive pressure at the time of the pass. -DRs and CODs led to decreases in pressure, especially when the starting pressure was higher. -Offensive players, including wide midfielders and strikers, perform more off-ball actions compared to players in other positions.

Table 10. Summary of Study Aims and Findings

Thesis Chapter	Study title	Aims	Findings
Chapter 6	Applying Positional Tracking Data to Improve Individual Passing Performance in 11v11 Football: A Pilot Study	To determine if metrics derived from positional tracking data (D-Def and Number of Outplayed Opponents) can be used to improve team passing performance using a video intervention	-The video intervention did not significantly improve performance. - The Intervention Team made greater numerical increases for the number of passes, penalty box entries, and shots on goal in the post-test match, supporting other studies that video feedback can be a useful tool for development. - Future work should include combining data-driven metrics with coaches' input to design training that encourages the desired behavior.

Chapter 4 analysed the level of football practitioners' awareness of data-driven metrics. Chapter 4 found that despite technological advances and new access to data, coaches and analysts still use and rely on metrics gathered via notational analysis centred around shooting metrics. This finding is in line with previous investigations showing the validity of shooting metrics with winning teams taking more shots and shots on goal with greater effectiveness than losing and drawing teams (Carlos Lago-Peñas et al., 2010; Szwarc, 2004a). The findings support the review by Drust et al. (Barry Drust & Matthew Green, 2013) in that the marriage between knowledge gained from research and its use in the "design, planning and implementation of the strategy" to the game is missing. Despite the continual rise in financial investment in football research and analytics (F. Goes et al., 2020; Rein & Memmert, 2016b), in the current thesis, practitioners were either uneducated about the newer metrics provided by data science or did not have access to data-driven KPIs (Chapter 4).

Further, previous investigations found that variability exists among practitioners regarding playing style and what defines success on the pitch (Meerhoff et al., 2019; Memmert et al., 2017). Although data science has primarily focused on passing metrics, passing and possession-based metrics that depend on positional tracking were reportedly used the least by practitioners (Chapter 4). This further supports the notion discussed by Cushion et al. (Cushion, Ford, & Williams, 2012), underlining the difference between the incentive of scientists to generate novelty versus the pressure to win felt by coaches and analysts. The enthusiasm of the academic community responsible for producing and promoting metrics and knowledge derived from data falls on deaf ears of practitioners in the thick of a competitive season.

In response to Chapter 3's discovery of a lack of research investigating off-ball actions of football players, this thesis contributes several novel findings to the literature. First, chapter 5 found evidence to support the use of positional tracking data to measure off-ball behaviour for prospective offensive potency. When exploring changes in pressure during two common off-ball behaviours (DRs and CODs), football players were able to alleviate defensive pressure, making them more likely to receive a pass. Further, compared to defensive positions, offensive players (wide midfielders and strikers) employed a higher frequency of off-ball movements, which led to greater decreases in pressure when the initial defensive pressure was higher. When closely marked by a defender in the opponent's half, it is likely that attacking players recognize there must be space available in other areas. Therefore, they prospectively exploit that space with movement. In contrast, when an attacking player is left unmarked, their running might take them into areas of higher pressure closer to the opponent's goal.

A team of researchers at the Barca Innovation Hub and Zelus Analytics also recognized that off-ball behaviour had been understudied in the data-driven analysis of player performance (Llana, Burriel, Madrero, & Fernández, 2022). By employing a speed signal of 21 km/h, the authors calculated player's velocity using a rolling average over different frames to identify the number of high-intensity runs and the distance covered at a high-intensity. Whereas in our approach (Chapter 5), we only looked at zones of the field, Lallana et al. classified runs into various tactical contexts, including the attack type (i.e., possession vs. counterattack) and defensive pressure type (i.e., high press versus sitting in a low defensive block). They could compare players of the same position within the same role across the Big-5 European competitions (English Premier League, Spanish La Liga, German Bundesliga, French Ligue 1, and Italian Serie A). Llana et al. determined that high-intensity runs positively influence expected possession value and expected goals (xG). This can also be deduced from the findings in Chapter 5, where we found that sprinting actions lead to decreases in defensive pressure during a time series. Less defensive pressure on the shooter and greater space was correlated to high pass reception (Chapter 5) and is an important factor in the chances of converting a goal-scoring opportunity (Anzer & Bauer, 2021; Schulze et al., 2018).

While nearly all data-driven approaches describe patterns and what has already occurred on the pitch, Chapter 6 made the first attempt to implement data-driven metrics to elicit improvements in football performance in a professional football setting. From this pilot intervention study design, it was discovered that providing football players with video feedback containing numerical values ranking their passes for D-Def (defensive destabilization) and Number of Outplayed Opponents failed to improve performance for these metrics. However, players on the Intervention Team made show improvements in more traditional key performance indicators (Mat Herold et al., 2021), including Number of Passes, Penalty Box Entries, Pass Length, and Shots on Goal. These findings have important implications for future research and applied work implementing data-driven metrics to improve performance. Whereas video feedback has proven to be an effective teaching tool (Groom & Cushion, 2005), previous investigations (Groom et al., 2011; Wright et al., 2012) did not introduce novel metrics nor objective measurements for specific behaviour such as passing performance. Therefore, to further understand the relationship between data-driven metrics and the developmental process, it is recommended that future work emulates previous studies (Harvey et al., 2010; Práxedes et al., 2019) and synchronizes the expertise of data scientists with coaches. Additionally, quantifying passing performance in a complex way that is not necessarily obvious to the player "in the heat of the battle" may require a longer experimental duration and more matches to show improvements. Perhaps the information provided by data science could be used to show general differences in pass types and relate them to individual and team performance.

7.2 Major contributions

This thesis makes significant contributions to theory, methodology and applied practice related to the use of data science in football. A discussion of each of these contributions is given below.

7.2.1 Contributions to Theory

Tactical behaviour, relevant to dynamic systems theory, has been defined as “the management of space and time by a group of cooperating individuals, in interaction with the opponent while constantly adapting to the conditions of play, in order to achieve a common goal” (F. Goes, Kempe, Van Norel, & Lemmink, 2021). This thesis, underpinned by a holistic ideology and dynamic systems theory approach to football, provides insight into the use and usefulness of data science in football. Chapters 3 and 4 showed that practitioners need more access and education surrounding the capabilities of data-driven approaches using positional tracking data. Chapter 5 demonstrated the ability of positional tracking to detect changes in pressure and showed a strong relationship between DRs and CODs and subsequent decreases in defensive pressure. Subsequently, Chapter 5 reinforced that the movement of players without the ball plays a vital role in the opportunity to play effective passes.

Chapter 6 revealed that access to positional tracking data alone is not enough to improve performance. It will take collaborative efforts between research and practice to transfer knowledge to the game. Together, these findings support the theoretical underpinnings of the thesis and add support to the dynamic systems theory of football (Fernandes, Camerino, Garganta, Pereira, & Barreira, 2019; Grehaigne et al., 1997). Of primary importance to dynamics systems theory related to football is the perspective of two teams competing in a variable environment (field, weather, surface, etc.) as a complex system (Grehaigne et al., 1997). Accordingly, this thesis attempted to ensure that the football players were analysed in the closest resemblance possible reflective of association football (i.e., 11v11 football match-play). In this way, constraining factors on positional tracking data could be investigated as the normal number of field players and field dimensions of professional football were maintained. As a result, the thesis provided insight into factors such as playing position and pitch area. The results found in Chapters 5 and 6 support the need for a similar spatiotemporal environment to maintain representative perception-action coupling.

7.2.2 Contributions to Methodology

This thesis supports the concept behind metrics previously developed using positional tracking data. Previously, research investigating positional tracking data in a football setting primarily studied passing behaviour (Power et al., 2017; Rein et al., 2017). Many of the studies on passing have focused on prediction. For example, Cintia et al. (2015) used passing metrics to predict match outcomes (win vs. draw vs. lose) in various European leagues with up to 60% accuracy (Cintia, Giannotti, Pappalardo, Pedreschi, & Malvaldi, 2015). However, there is little that coaches and analysts can take from those studies for their decision-making process. As positional tracking data affords the simultaneous examination of all 22 players on the field, the ability to study specific tactical principles of play becomes possible.

According to dynamic systems theory, tactical principles equate to how much space and time players have available to make decisions and execute their chosen skills. As such, studies have been done examining space control (Rein et al., 2016) and pressure, using a model by Andrienko et al. (Andrienko et al., 2017). In this thesis, we modified the pressure model for use in our off-ball study (Chapter 5). In Chapter 6, we incorporated an existing defensive destabilization model known as D-Def (F. R. Goes et al., 2018) and Number of Outplayed Opponents (NOO) (Steiner et al., 2019). The defensive pressure model was previously used to measure pressure on the ball carrier; however, Chapter 5 successfully adapted the model to examine pressure on players without the ball.

Finally, Chapter 6 pioneered an effort to bring knowledge acquired by positional tracking data science to the football pitch to improve performance. In doing so, a new method to integrate data was formulated and implemented for the first time. The way we analysed passes on an individual level resulted in feedback for players that is objective and more accurate than previously used notational methods. Further, the processing speed required far less time to process data, enabling multiple player's data analysis with fast turnaround times. Therefore, this study brought the possible value of positional tracking data to the forefront of player development. However, the hurdles of an intervention study at the professional level were encountered as the aims of science had to blend with the constraints presented by the primary motivation (and pressure) to win. The results showed that a short-term video intervention was not particularly effective. In addition to a lengthier intervention, it could be fruitful to incorporate the coaching staff to develop ways to train the desired behaviour.

7.2.3 Contributions to Applied Practice

Contributions from this thesis can be interpreted and used in the applied setting in many ways. Using positional tracking data and algorithms to quantify tactical performance presents opportunities to improve: i) providing coaches and analysts with an objective view of training and match analysis in a dynamic context and ii) training design and player development.

i. Providing coaches and analysts with an objective view of training and match analysis in a dynamic context

Player tracking has mostly been utilized to quantify workload and running-related metrics, aiming to optimise performance and minimize the risk of injury (Gabbett, 2020; Jaspers, Brink, Probst, Frencken, & Helsen, 2017). While measures such as high-speed running distance and acceleration load can be vaguely related to tactical play, they do not provide coaches and analysts insight into decision-making in various match contexts. With positional tracking, this can be done by showing information such as player movement trajectories during key moments of the match (Roger Bartlett, Button, Robins, Dutt-Mazumder, & Kennedy, 2012)and positional variability using heat maps (Moura et al., 2015). While the way D-Def and NOO were used in this thesis did lead to significant results, we showed they could efficiently be used in the educational process of player development. Furthermore, we showed that using positional tracking data to quantify tactical behaviour allows practitioners to quickly obtain quantitative data about who is producing results among various key performance indicators. Although further research is needed to continue improving the application of data science in football, it is probable that more clubs will follow the likes of Liverpool FC and lean on lead data analytics as an integral part of coaches and analysts' overall preparation (Pinto, 2021).

ii. Training design and player development

To maximize player development, coaches must design training sessions that place realistic demands on players. The training environment should expose players to the contextual interactions of match-play and, through constraints, provoke players to develop solutions to various problems (D. Araújo et al., 2010; Davids et al., 2012). To design training in this way, coaches need to understand the key performance indicators that influence the outcome of matches and the ability to quantify these actions. By keeping track of metrics for each game (and perhaps training sessions, an area where in Chapter 4 it was discovered is lacking), coaches can continuously inform themselves and players about their performance and identify strengths and areas of need. The short period required between data collection and reporting could allow coaches to modify training from session-to-session, resulting in a practical method to advise training design for optimal player development. Furthermore, this thesis provides a rationale for measuring certain key performance indicators and metrics gathered by tracking data that may be used as standards for different age groups and positions of play.

7.3 Research Strengths

The strength of this thesis can be summarised as an advancement of the current understanding of the use and usefulness of data science in a representative football environment. Insofar as this organisation of research broadens previous literature in several ways.

i. The body of work in this thesis was developed from a sound theoretical background of how football players and teams interact in a football match. The dynamic systems approach to tactical analysis considers the variable characteristics of both the individual player and team environment. Thus, the design of the studies is representative of the organic football environment. As such, the findings from the presented work can be generalised to the association football environment.

ii. The thesis addresses relevant football tactics. Key performance indicators, including off-ball behaviour and passing metrics, are considered key skills in football (Michael Hughes et al., 2012; Silva, Garganta, Santos, & Teoldo, 2014; Yang et al., 2018). The findings from this research provide a basis for future studies and insight into integrating data science into practice. This includes the combination of notational analysis with positional tracking data.

iii. Positional tracking data was used to quantify players' off-ball behaviour and passing performance in Chapters 5 and 6. Positional tracking enabled 1) highly accurate data collection compared to previous notational analysis methods, 2) time-efficient data collection and analysis compared to previous notational analysis methods, and 3) the ability to quantify novel aspects of off-ball behaviour and the effect of the behaviour on the opposition.

iv. Chapters 5 and 6 utilised validated approaches (Andrienko et al., 2017; F. R. Goes et al., 2018; Rein et al., 2017) to analyse tactical performance obtained from tracking data, resulting in objective and reproducible data analysis. Therefore, the results from these analysis methods are not influenced by subjective bias and can easily be compared between studies using the same approaches.

v. Chapter 5 utilised a novel, combined approach of notational analysis with positional tracking data. In doing so, the football players' finely tuned off-ball actions and the resultant effect on the defense could be investigated in a professional environment.

vi. Chapter 6 investigated the effect of a video intervention on players passing performance in their natural environment, 11v11 football match-play. Though the results were insignificant, the study presented a realistic representation of the challenges associated with integrating data science into football.

7.4 Research Limitations

This thesis presents novel research offering theoretical, methodological, and practical contributions to the field. Nonetheless, there are limitations associated with the design and methodology that should be addressed in correspondence to the findings. Several of these limitations are a result of a relatively new research area. To provide stronger evidence in this area of research in the future, the limitations of this thesis are outlined below.

i. Due to the decision to focus on machine learning in football, only research using software to investigate the tactical behaviour of football players was included in the narrative review of the literature (Chapter 3). Therefore, research examining these aspects using notational or observational methods was excluded from the review, as were investigations with machine learning in other sports. To account for this and to provide a more detailed description of tactical play, Chapter 1 discussed known research on football tactics stemming from the notational analysis.

ii. The dataset used in Chapter 5 consisted solely of players on the German National Team and their opponents. As a result, the findings represent the participants involved in the studies at the time of data collection. While the findings supported the theoretical underpinnings of the studies, the results may differ if subjects from different training regimes, tactics and strategies, or socio-cultural backgrounds were used.

iii. Due to difficulties with the quality of the positional tracking data, data for each match in Chapter 5 was collected at random times over several years. In addition, data for Chapter 6 was collected for only one team over a short period during the middle of a professional playing season. Therefore, the results may differ if more teams were used at different times and for longer periods.

iv. In Chapter 6, sampled players were aware that their passes were being evaluated for a scientific study. Therefore, their passing decisions and execution may have changed in response to the experimental nature of the data collection.

7.5 Future Research

This thesis has further developed research examining football data science and machine learning. However, integrating data science in practical settings is still a work in progress. In particular, research investigating data science to improve performance is scarce. To improve the practical applications of this research, it is recommended that future research focuses on building upon this thesis and earlier work on data science in football. The ideas presented below will hopefully bring pertinent benefits to various football levels and environments.

As the playing field levels in terms of technical skills and athleticism due to the increased popularity of sports science (strength training, nutrition, player load monitoring, etc.), tactical play will continue to be where football coaches and analysts differentiate themselves (Memmert et al., 2017; Weldon et al., 2021). Thus, there is a demand to provide evidence that using data-driven tools and resources can improve their players' and teams' performance. More research about how various metrics can be used in practitioners' daily work is needed. It is recommended that this investigation considers 1) ways in which using tactical metrics influences the design of training, 2) the transfer of data-driven training to match-play, 3) any subsequent performance improvements resulting from the use of positional tracking data, and 4) how data-driven key performance indicators evolve as the game develops over time.

Chapter 5 analysed off-ball behaviour and its importance in reducing defensive pressure. As much of football's intricacies occur without the ball, a deeper understanding of off-ball behaviour is still needed (Fernandez & Bornn, 2018). Some research has shown that the positioning and movements of pass recipients play a role in the outcome of passes (Silvan Steiner, 2018; Steiner et al., 2019); however, this work can be extended further. For example, combine some of the findings in Chapter 5 with factors such as zone of the pitch or examine how multiple player movements interact in creating space relative to the opponent. In the future, the passing risk versus reward model could be integrated with an off-ball pressure model to give a full picture of the value of the off-ball action as it relates to the reward of passes (Fernández et al., 2019; Floris Goes et al., 2021). Improvements in offensive positioning, relieving defensive pressure, and creating more high-probability goal-scoring situations are all likely to improve with a greater understanding of off-ball behaviour gained from positional tracking data.

The current thesis uses positional tracking data to measure the outcome of passes and off-ball behaviour. In Chapter 6, we examined how players' passing performance changed based on a video intervention in a professional setting. Due to previously mentioned limitations in the study design, we recommend future studies consist of more extensive interventions, including the collaboration with coaches to come up with pertinent drills related to eliciting the desired outcome. Further, passing performance relies on individual actions within the team coordination context (Silva et al., 2014; L. Vilar et al., 2012), including the synergy between players (W. Frencken et al., 2012). Instead of looking at isolated passes, it could prove useful to examine changes in individual passing performance related to factors such as team centroid (the average position of the outfield players) or different phases of play. In addition, it would be fruitful to determine how passing performance improvements influence key performance indicators such as shots on goal or xG. Efforts to determine what kind of educational process benefits player development, such as comparing different types of video interventions, various types of training drills with and without opposition, etc., is another next step necessary to further understand how data-driven metrics can be used to improve football performance. One example is creating different small-sided games containing the varying number of players, field sizes, and other rules that will influence the physical, technical and tactical demands(Owen et al., 2004). After exposure to different constraints and types of play, players would be assessed on their performance for the chosen metrics.

Finally, given the exhaustive nature of football, technical performance has been shown to change according to phases of the match related to states of fatigue (Harper, West, Stevenson, & Russell, 2014; Rampinini et al., 2009). Therefore, it makes sense to assume that weakened physiological states may also be directly related to changes in the tactics used by football players and teams. Understanding the relationship between fatigue and tactical performance in a football context could have important outcomes for applied settings. As suggested by Memmert et al. (2017) (Memmert et al., 2017), it would be useful to use positional tracking data to determine how tactics change or how coaches modify their strategy to cope with increasing fatigue. A study combining GPS running data with tactical data could prove insightful to coaches and analysts who want to identify patterns of play in their own team and that of their opponent during different times of the match.

7.6 Conclusions

This thesis, and the studies included within it, represent a substantial contribution to a rapidly growing field of research. Though the findings contribute greatly to our understanding of the use and usefulness of data science in a football setting, there remain several unanswered questions that should be addressed in future research. The thesis has made strong contributions to the status quo of positional tracking data at various game levels, developed, and implemented new models to examine off-ball behaviour, and pioneered research in relation to implementing data science in football. Chiefly, this thesis adds support to the dynamic systems theory of football. With more and faster access to objective data, coaches and analysts can make tactical decisions and strategize more quickly, including adjusting their training plans.

Further, the pressure model presented in Chapter 5 and the data-driven metrics discussed and utilized in this thesis can influence the match analysis and training processes. While the findings of this thesis show that there is a way to go in bridging the gap between data science research and practice, it does give an understanding of *how* the use of data can assist what coaches and analysts already do. This is important because the speed and quality of information the football staff receive determines the *capability* of making more informed decisions. Additionally, these findings provide an evidence base to inform future investigations of the use of data science in a football environment.

References

Acar, M., Yapicioglu, B., Arikan, N., Yalcin, S., Ates, N., & Ergun, M. (2008). Analysis of goals scored in the 2006 World Cup. In *Science and football VI* (pp. 261-268): Routledge.

Adams, D., Morgans, R., Sacramento, J., Morgan, S., & Williams, M. D. (2013). Successful short passing frequency of defenders differentiates between top and bottom four English Premier League teams. *International Journal of Performance Analysis in Sport, 13*(3), 653-668.

Akenhead, R., Hayes, P. R., Thompson, K. G., & French, D. (2013). Diminutions of acceleration and deceleration output during professional football match play. *Journal of science and medicine in sport, 16*(6), 556-561.

Akenhead, R., & Nassis, G. P. (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.

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

Almeida, C. H., Duarte, R., Volossovitch, A., & Ferreira, A. P. (2016). Scoring mode and age-related effects on youth soccer teams' defensive performance during small-sided games. *Journal of Sports Sciences, 34*(14), 1355-1362.

Almeida, C. H., Ferreira, A. P., & Volossovitch, A. (2014). Effects of match location, match status and quality of opposition on regaining possession in UEFA Champions League. *Journal of human kinetics, 41*, 203.

Alves, D. L., Osiecki, R., Palumbo, D. P., Moiano-Junior, J. V., Oneda, G., & Cruz, R. (2019). What variables can differentiate winning and losing teams in the group and final stages of the 2018 FIFA World Cup? *International Journal of Performance Analysis in Sport, 19*(2), 248-257.

Amatria, M., Dios, R. M., Pérez-Turpin, J. A., Gomis-Gomis, M. J., Elvira-Aranda, C., & Suárez-Llorca, C. (2019). Technical-Tactical Analysis of The Players of the Left and Right Wing in Elite Soccer. *Journal of human kinetics, 70*(1), 233-244.

Aminikhanghahi, S., & Cook, D. J. (2017). A survey of methods for time series change point detection. *Knowledge and information systems, 51*(2), 339-367.

Andrienko, G., Andrienko, N., Budziak, G., Dykes, J., Fuchs, G., von Landesberger, T., & Weber, H. (2017). Visual analysis of pressure in football. *Data Mining and Knowledge Discovery, 31*(6), 1793-1839.

Anzer, G., & Bauer, P. (2021). A goal scoring probability model for shots based on synchronized positional and event data in football (soccer). *Frontiers in Sports and Active Living, 3*, 624475.

Araújo, D., Fonseca, C., Davids, K., Garganta, J., Volossovitch, A., Brandão, R., & Krebs, R. (2010). The role of ecological constraints on expertise development. *Talent Development and Excellence, 2*(2), 165-179.

Araújo, R., Mesquita, I., Hastie, P., & Pereira, C. (2016). Students' game performance improvements during a hybrid sport education–step-game-approach volleyball unit. *European Physical Education Review, 22*(2), 185-200.

Araya, J. A., & Larkin, P. (2013). Key performance variables between the top 10 and bottom 10 teams in the English Premier League 2012/13 season. *Human Movement, Health and Coach Education (HMHCE), 2*, 17-29.

Armatas, V., & Pollard, R. (2014). Home advantage in Greek football. *European Journal of Sport Science, 14*(2), 116-122.

Armatas, V., & Pollard, R. (2014). Home advantage in Greek football. *Eur J Sport Sci, 14*(2), 116-122. doi:10.1080/17461391.2012.736537

Armatas, V., & Yiannakos, A. (2010). Analysis and evaluation of goals scored in 2006 World Cup. *Journal of Sport and Health Research, 2*(2), 119-128.

Arnason, A., Sigurdsson, S. B., Gudmundsson, A., Holme, I., Engebretsen, L., & Bahr, R. (2004). Physical fitness, injuries, and team performance in soccer. *Medicine and science in sports and exercise, 36*(2), 278-285.

Aughey, R. J. (2011). Applications of GPS technologies to field sports. *International journal of sports physiology and performance, 6*(3), 295-310.

Ávila-Moreno, F. M., Chirosa-Ríos, L. J., Urena-Espa, A., Lozano-Jarque, D., & Ulloa-Diaz, D. (2018). Evaluation of tactical performance in invasion team sports: a systematic review. *International Journal of Performance Analysis in Sport, 18*(2), 195-216.

Balyan, M., Vural, F., Catikkas, F., Yucel, T., Afacan, S., Atik, E., & Acar, M. (2007). Technical analysis of 2006 World Cup soccer champion Italy. *J Sports Sci Med, 10*, 4-5.

Bangsbo, J. (1994). The physiology of soccer--with special reference to intense intermittent exercise. *Acta physiologica scandinavica. Supplementum, 619*, 1-155.

Bangsbo, J., Iaia, F. M., & Krustrup, P. (2007). Metabolic response and fatigue in soccer. *International journal of sports physiology and performance, 2*(2), 111-127.

Baptista, I., Johansen, D., Figueiredo, P., Rebelo, A., & Pettersen, S. A. (2019). Positional differences in peak-and accumulated-training load relative to match load in elite football. *Sports, 8*(1), 1.

Barnes, C., Archer, D., Hogg, B., Bush, M., & 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.

Barron, D., Ball, G., Robins, M., & Sunderland, C. (2018). Artificial neural networks and player recruitment in professional soccer. *PloS one, 13*(10), e0205818.

Barte, J. C., Nieuwenhuys, A., Geurts, S. A., & Kompier, M. A. (2020). Effects of fatigue on interception decisions in soccer. *International Journal of Sport and Exercise Psychology, 18*(1), 64-75.

Bartlett, R., Button, C., Robins, M., Dutt-Mazumder, A., & Gavin, K. (2012). Analysing team coordination patterns from player movement trajectories in soccer: methodological considerations. *Int. J. Perform. Anal. Sport, 12*(27), 398-424.

Bartlett, R., Button, C., Robins, M., Dutt-Mazumder, A., & Kennedy, G. (2012). Analysing team coordination patterns from player movement trajectories in soccer: Methodological considerations. *International Journal of Performance Analysis in Sport, 12*(2), 398-424.

Bate, R. (1988). Football chance: tactics and strategy. *T. Reilly, A. Lees, K. Davids e*.

Bell-Walker, J., McRobert, A., Ford, P., & Williams, M. (2006). Quantitative analysis of successful teams at the 2006 World Cup Finals. *Insight–The FA Coaches Association Journal, 6*(4), 36-43.

Bialkowski, A., Lucey, P., Carr, P., Matthews, I., Sridharan, S., & Fookes, C. (2016). Discovering team structures in soccer from spatiotemporal data. *IEEE Transactions on Knowledge and Data Engineering, 28*(10), 2596-2605.

Bialkowski, A., Lucey, P., Carr, P., Yue, Y., & Matthews, I. (2014). *Win at home and draw away: Automatic formation analysis highlighting the differences in home and away*

team behaviors. Paper presented at the Proceedings of 8th annual MIT sloan sports analytics conference.
Bialkowski, A., Lucey, P., Carr, P., Yue, Y., Sridharan, S., & Matthews, I. (2014a). *Large-Scale Analysis of Soccer Matches Using Spatiotemporal Tracking Data*.
Bialkowski, A., Lucey, P., Carr, P., Yue, Y., Sridharan, S., & Matthews, I. (2014b). *Large-scale analysis of soccer matches using spatiotemporal tracking data.* Paper presented at the 2014 IEEE International Conference on Data Mining (ICDM).
Bloomfield, J., Jonsson, G., Polman, R., Houlahan, K., & O'Donoghue, P. (2005). Temporal pattern analysis and its applicability in soccer. In L. Anolli, S. Duncan, M. Magnusson, & G. Riva (Eds.), *The hidden structure of social interaction: from genomics to cultural patterns* (pp. 237-251). Amsterdam: IOS Press.
Bondia, I. L., González-Rodenas, J., Moreno, F. C., Pérez-Turpin, J. A., & Malavés, R. A. (2017). Creating goal scoring opportunities in elite soccer. Tactical differences between Real Madrid CF and FC Barcelona. *RETOS. Nuevas Tendencias en Educación Física, Deporte y Recreación*(32), 233-237.
Borrie, A., Jonsson, G. K., & Magnusson, M. S. (2002). Temporal pattern analysis and its applicability in sport: an explanation and exemplar data. *Journal of sports sciences, 20*(10), 845-852.
Bradley, P. S., Carling, C., Archer, D., Roberts, J., Dodds, A., Di Mascio, M., . . . Krustrup, P. (2011). The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. *Journal of sports sciences, 29*(8), 821-830.
Bransen, L., Van Haaren, J., & van de Velden, M. (2019). Measuring soccer players' contributions to chance creation by valuing their passes. *Journal of Quantitative Analysis in Sports, 15*(2), 97-116.
Brink, M. S., Kuyvenhoven, J. P., Toering, T., Jordet, G., & Frencken, W. G. (2018). What do football coaches want from sport science? *Kinesiology, 50*(1), 150-154.
Brito, Â., Roriz, P., Silva, P., Duarte, R., & Garganta, J. (2017). Effects of pitch surface and playing position on external load activity profiles and technical demands of young soccer players in match play. *International Journal of Performance Analysis in Sport, 17*(6), 902-918.
Brooks, J., Kerr, M., & Guttag, J. (2016). Using machine learning to draw inferences from pass location data in soccer. *Stat. Anal. Data Min., 5*(9), 338-349.
Brud, L. (2017). The International Football Association Board. 2015 May. *Amendments to the laws of the game-2015/2016 and information on the completed reform of The International Football Association Board URL: http://resources. fifa. com/mm/document/affederation/ifab/02/60/91/38/circular_log_amendments_2015_v1 . 0_en_neutral. pdf [accessed 2017-02-19][WebCite Cache ID 6yQEWMtkL].*
Brughelli, M., Cronin, J., Levin, G., & Chaouachi, A. (2008). Understanding change of direction ability in sport. *Sports medicine, 38*(12), 1045-1063.
Brümmer, K. (2018). Subjectivation by video—ethnographic explorations on practices of video analysis in high-performance youth football. *German Journal of Exercise and Sport Research, 48*(3), 358-365.
Buchheit, M., Allen, A., Poon, T. K., Modonutti, M., Gregson, W., & Di Salvo, V. (2014). 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.

Buchheit, M., & Simpson, B. M. (2017). Player-tracking technology: half-full or half-empty glass? *International journal of sports physiology and performance, 12*(s2), S2-35-S32-41.

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

Carling, C. (2011). Influence of opposition team formation on physical and skill-related performance in a professional soccer team. *European Journal of Sport Science, 11*(3), 155-164.

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

Carling, C., Le Gall, F., McCall, A., Nedelec, M., & Dupont, G. (2015). Squad management, injury, and match performance in a professional soccer team over a championship-winning season. *Eur. J. Sport Sci., 15*(7), 573-582.

Carling, C., Reilly, T., & Williams, A. M. (2008). *Performance assessment for field sports*. London: Routledge.

Carling, C., Williams, A. M., & Reilly, T. (2007). *Handbook of soccer match analysis: A systematic approach to improving performance*: Routledge.

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

Casadesus-Masanell, R., & Ricart, J. E. (2010). From strategy to business models and onto tactics. *Long range planning, 43*(2-3), 195-215.

Casal, C. A., Losada López, J. L., & Ardá Suárez, A. (2015). Análisis de los factores de rendimiento de las transiciones ofensivas en el fútbol de alto nivel.

Casal, C. A., Maneiro, R., Ardá, T., Marí, F. J., & Losada, J. L. (2017). Possession zone as a performance indicator in football. The Game of the Best Teams. *Frontiers in psychology, 8*, 1176.

Castañer, M., Barreira, D., Camerino, O., Anguera, M. T., Canton, A., & Hileno, R. (2016). Goal scoring in soccer: a polar coordinate analysis of motor skills used by Lionel Messi. *Frontiers in psychology*, 806.

Castellano-Paulis, J., Hernández-Mendo, A., Morales-Sanchez, V., & Anguera-Argilaga, M. (2007). Optimising a probabilistic model of the development of play in soccer. *Quality & Quantity, 41*(1), 93-104.

Castellano, J., Alvarez-Pastor, D., & Bradley, P. S. (2014). Evaluation of research using computerised tracking systems (Amisco® and Prozone®) to analyse physical performance in elite soccer: A systematic review. *Sports Medicine, 44*(5), 701-712.

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*, 137-147.

Cervone, D., D'Amour, A., Bornn, L., & Goldsberry, K. (2014). *POINTWISE: Predicting points and valuing decisions in real time with NBA optical tracking data.* Paper presented at the Proceedings of the 8th MIT Sloan Sports Analytics Conference, Boston, MA, USA.

Chassy, P. (2013). Team play in football: How science supports FC Barcelona's training strategy. *Psychology, 4*(9), 7.

Chawla, S., Estephan, J., Gudmundsson, J., & Horton, M. (2017). Classification of passes in football matches using spatiotemporal data. *ACM Transactions on Spatial Algorithms and Systems (TSAS), 3*(2), 1-30.

Cintia, P., Giannotti, F., Pappalardo, L., Pedreschi, D., & Malvaldi, M. (2015). *The harsh rule of the goals: Data-driven performance indicators for football teams.* Paper presented at the 2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA).

Ciocca, G., Tessitore, A., Mandorino, M., & Tschan, H. (2022). A Video-Based Tactical Task Does Not Elicit Mental Fatigue and Does Not Impair Soccer Performance in a Subsequent Small-Sided Game. *Sports, 10*(3), 31.

Clemente, F. (2012). Study of successful teams on FIFA World Cup 2010 through notational analysis. *Pamukkale Spor Bilimleri Dergisi, 3*(3), 90-103.

Clemente, F. M., Couceiro, M. S., Martins, F., & Mendes, R. (2013). An online tactical metrics applied to football game. *Res. J. Appl. Sci. Eng. Technol., 5*(5), 1700-1719.

Clemente, F. M., Couceiro, M. S., Martins, F. M. L., Dias, G., & Mendes, R. (2013). Interpersonal dynamics: 1v1 sub-phase at sub-18 football players. *Journal of Human Kinetics, 36*, 179.

Clemente, F. M., Martins, F. M. L., Kalamaras, D., Wong, P. D., & Mendes, R. S. (2015). General network analysis of national soccer teams in FIFA World Cup 2014. *International Journal of Performance Analysis in Sport, 15*(1), 80-96.

Cohen, J. New York, NY: Routledge Academic; 1988. *Statistical Power Analysis for the Behavioral Sciences.[Google Scholar]*.

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.

Couceiro, M. S., Clemente, F. M., Martins, F. M., & Machado, J. A. T. (2014). Dynamical stability and predictability of football players: the study of one match. *Entropy, 16*(2), 645-674.

Coutinho, D., Gonçalves, B., Santos, S., Travassos, B., Wong, D. P., & Sampaio, J. (2019). Effects of the pitch configuration design on players' physical performance and movement behaviour during soccer small-sided games. *Research in Sports Medicine, 27*(3), 298-313.

Coutts, A. J. (2016). Working fast and working slow: the benefits of embedding research in high-performance sport. *International journal of sports physiology and performance, 11*(1), 1-2.

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

D., B., Garganta, J., Guimarães, P., Machado, J., & Anguera, M. T. (2014). Ball recovery patterns as a performance indicator in elite soccer. *J Sports Eng. Technol., 228*(1), 61-72.

Davids, K., Araújo, D., Hristovski, R., Passos, P., & Chow, J. Y. (2012). Ecological dynamics and motor learning design in sport. *Skill acquisition in sport: Research, theory and practice*, 112-130.

Dellal, A., Chamari, K., Wong, d. P., Ahmaidi, S., Keller, D., Barros, R., . . . Carling, C. (2011). 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., 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.

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

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*(03), 205-212.

Dong, Y., & Peng, C. Y. (2013). Principled missing data methods for researchers. *Springerplus, 2*(1), 222. doi:10.1186/2193-1801-2-222

Dos'Santos, T., Thomas, C., Comfort, P., & Jones, P. A. (2018). The effect of angle and velocity on change of direction biomechanics: An angle-velocity trade-off. *Sports Medicine, 48*(10), 2235-2253.

Drust, B., & Green, M. (2013). Science and football: evaluating the influence of science on performance. *J. Sports Sci., 31*(13), 1377-1382.

Drust, B., & Green, M. (2013). Science and football: evaluating the influence of science on performance. *Journal of sports sciences, 31*(13), 1377-1382.

Duarte, R., Araújo, D., Correia, V., & Davids, K. (2012). Sports teams as superorganisms. *Sports Medicine, 42*(8), 633-642.

Duarte, R., Araújo, D., Davids, K., Travassos, B., Gazimba, V., & Sampaio, J. (2012). Interpersonal coordination tendencies shape 1-vs-1 sub-phase performance outcomes in youth soccer. *Journal of sports sciences, 30*(9), 871-877.

Duarte, R., Araujo, D., Gazimba, V., Fernandes, O., Folgado, H., Marmeleira, J., & Davids, K. (2010). The ecological dynamics of 1v1 sub-phases in association football. *The Open Sports Sciences Journal, 3*(1).

Duch, J., Waitzman, J. S., & Amaral, L. A. N. (2010). Quantifying the performance of individual players in a team activity. *PloS one, 5*(6).

Dufour, M., Phillips, J., & Ernwein, V. (2017). What makes the difference? Analysis of the 2014 World Cup. *Journal of Human Sport and Exercise, 12*(3), 616-629.

Eggels, R. v. E. H., & Pechenizkiy, M. (2016). *Explaining soccer match outcomes with goal scoring opportunities predictive analytics.* Paper presented at the 3rd Workshop on Machine Learning and Data Mining for Sports Analytics, Riva del Garda, Italy.

El-Kotob, R., & Giangregorio, L. M. (2018). Pilot and feasibility studies in exercise, physical activity, or rehabilitation research. *Pilot and feasibility studies, 4*(1), 1-7.

Ensum, J., Pollard, R., & Taylor, S. (2004). Applications of logistic regression to shots at goal in association football: Calculation of shot probabilities, quantification of factors and player/team. *Journal of Sports Sciences, 22*(6), 500-520.

Fairchild, A., Pelechrinis, K., & Kokkodis, M. (2018). Spatial analysis of shots in MLS: a model for expected goals and fractal dimensionality. *Journal of Sports Analytics, 4*(3), 165-174.

Faisal, S., & Tutz, G. (2021). Multiple imputation using nearest neighbor methods. *Information Sciences, 570*, 500-516.

Faude, O., Koch, T., & Meyer, T. (2012). Straight sprinting is the most frequent action in goal situations in professional football. *Journal of Sports Sciences, 30*(7), 625-631.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav Res Methods, 39*(2), 175-191. doi:10.3758/bf03193146

Ferguson, C. J. (2009). An Effect Size Primer: A Guide for Clinicians and Researchers. *Professional Psychology: Research and Practice, 40*, 532-538. doi:10.1037/a0015808

Fernandes, T., Camerino, O., Garganta, J., Pereira, R., & Barreira, D. (2019). Design and validation of an observational instrument for defence in soccer based on the Dynamical Systems Theory. *International Journal of Sports Science & Coaching, 14*(2), 138-152.

Fernandez-Navarro, J., Fradua, L., Zubillaga, A., Ford, P. R., & McRobert, A. P. (2016). Attacking and defensive styles of play in soccer: analysis of Spanish and English elite teams. *Journal of sports sciences, 34*(24), 2195-2204.

Fernandez-Navarro, J., Fradua, L., Zubillaga, A., & McRobert, A. P. (2018). Influence of contextual variables on styles of play in soccer. *International Journal of Performance Analysis in Sport, 18*(3), 423-436.

Fernandez, J., & Bornn, L. (2018). *Wide Open Spaces: A statistical technique for measuring space creation in professional soccer.* Paper presented at the Proceedings of the Sloan Sports Analytics Conference.

Fernández, J., Bornn, L., & Cervone, D. (2019). *Decomposing the Immeasurable Sport: A deep learning expected possession value framework for soccer.* Paper presented at the 13th MIT Sloan Sports Analytics Conference.

Fernando, T., Wei, X., Fookes, C., Sridharan, S., & Lucey, P. (2015). *Discovering methods of scoring in soccer using tracking data.* Paper presented at the KDD Workshop on Large-Scale Sports Analytics, Sydney.

Feuerhake, U. (2016). Recognition of repetitive movement patterns—the case of football analysis. *ISPRS Int. J. Geo-Inf., 5*(11), 208.

Fleiss, J. L. (1971). Measuring nominal scale agreement among many raters. *Psychological bulletin, 76*(5), 378.

Flynn, T. (2001). The effects of crosses across three levels of professional football. *Insight: The FA Coaches Association Journal, 4*(2), 13-16.

Folgado, H., Lemmink, K. A., Frencken, W., & Sampaio, J. (2014). Length, width and centroid distance as measures of teams tactical performance in youth football. *European Journal of Sport Science, 14*(sup1), S487-S492.

Forcher, L., Forcher, L., Jekauc, D., Woll, A., Gross, T., & Altmann, S. (2022). Center backs work hardest when playing in a back three: The influence of tactical formation on physical and technical match performance in professional soccer. *PLoS One, 17*(3), e0265501.

Forcher, L., Kempe, M., Altmann, S., Forcher, L., & Woll, A. (2021). The "Hockey" Assist Makes the Difference—Validation of a Defensive Disruptiveness Model to Evaluate Passing Sequences in Elite Soccer. *Entropy, 23*(12), 1607.

Fradua, L., Zubillaga, A., Caro, Ó., Iván 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.

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

Frencken, W., Poel, H. d., Visscher, C., & Lemmink, K. (2012). Variability of inter-team distances associated with match events in elite-standard soccer. *Journal of sports sciences, 30*(12), 1207-1213.

Frencken, W. G., Lemmink, K. A., & Delleman, N. J. (2010). Soccer-specific accuracy and validity of the local position measurement (LPM) system. *Journal of science and medicine in sport, 13*(6), 641-645.

Frias, T., & Duarte, R. (2014). Man-to-man or zone defense? Measuring team dispersion behaviors in small-sided soccer games. *Trends in Sport Sciences, 21*(3), 135.

Fujimura, A., & Sugihara, K. (2005). Geometric analysis and quantitative evaluation of sport teamwork. *Systems and Computers in Japan, 36*(6), 49-58.

Gabbett, T. J. (2020). Debunking the myths about training load, injury and performance: empirical evidence, hot topics and recommendations for practitioners. *British journal of sports medicine, 54*(1), 58-66.

Gama, J., Passos, P., Davids, K., Relvas, H., Ribeiro, J., Vaz, V., & Dias, G. (2014). Network analysis and intra-team activity in attacking phases of professional football. *International Journal of Performance Analysis in Sport, 14*(3), 692-708.

García-González, L., Moreno, A., Gil, A., Moreno, M. P., & Villar, F. D. (2014). Effects of decision training on decision making and performance in young tennis players: An applied research. *Journal of Applied Sport Psychology, 26*(4), 426-440.

Garganta, J. (2009). Trends of tactical performance analysis in team sports: bridging the gap between research, training and competition. *Revista Portuguesa de Ciências do Desporto, 9*(1), 81-89.

Garganta, J., Maia, J., & Basto, F. (1997). Analysis of goal-scoring patterns in European top level soccer teams. *Science and football III*, 246-250.

Goes, F., Kempe, M., & Lemmink, K. (2019). Predicting match outcome in professional Dutch soccer using tactical performance metrics computed from position tracking data.

Goes, F., Kempe, M., Van Norel, J., & Lemmink, K. (2021). Modelling team performance in soccer using tactical features derived from position tracking data. *IMA Journal of Management Mathematics, 32*(4), 519-533.

Goes, F., Meerhoff, L., Bueno, M., Rodrigues, D., Moura, F., Brink, M., . . . Torres, R. (2020). Unlocking the potential of big data to support tactical performance analysis in professional soccer: A systematic review. *European Journal of Sport Science*, 1-16.

Goes, F., Schwarz, E., Elferink-Gemser, M., Lemmink, K., & Brink, M. (2021). A risk-reward assessment of passing decisions: comparison between positional roles using tracking data from professional men's soccer. *Science and Medicine in Football*, 1-9.

Goes, F. R., Kempe, M., Meerhoff, L. A., & Lemmink, K. (2018). Not every pass can be an assist: A data-driven model to measure pass effectiveness in professional soccer matches. *Big Data*. doi:10.1089/big.2018.0067

Goes, F. R., Kempe, M., Meerhoff, L. A., & Lemmink, K. (2019). Not Every Pass Can Be an Assist: A Data-Driven Model to Measure Pass Effectiveness in Professional Soccer Matches. *Big Data, 7*(1), 57-70. doi:10.1089/big.2018.0067

Gómez, M. A., Gómez-Lopez, M., Lago, C., & Sampaio, J. (2012). Effects of game location and final outcome on game-related statistics in each zone of the pitch in professional football. *European Journal of Sport Science, 12*(5), 393-398.

Gonçalves, B., Coutinho, D., Santos, S., Lago-Penas, C., Jiménez, S., & Sampaio, J. (2017). Exploring team passing networks and player movement dynamics in youth association football. *PLoS One, 12*(1), e0171156.

Grant, A., & Williams, M. (1999). Analysis of the final 20 matches played by Manchester United in the 1998–99 season. *Insight, 3*(1), 42-45.

Grehaigne, J.-F., Bouthier, D., & David, B. (1997). Dynamic-system analysis of opponent relationships in collective actions in soccer. *J. Sports Sci., 15*(2), 137-149.

Gréhaigne, J., Wallian, N., & Godbout, P. (2005). Tactical-decision learning model and students' practices. *Physical Education and Sport Pedagogy, 10*(3), 255-269.

Groom, R., & Cushion, C. (2005). Using of video based coaching with players: A case study. *International Journal of Performance Analysis in Sport, 5*(3), 40-46.

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.

Grund, T. U. (2012). Network structure and team performance: The case of English Premier League soccer teams. *Social Networks, 34*(4), 682-690.

Grunz, A., Memmert, D., & Perl, J. (2012). Tactical pattern recognition in soccer games by means of special self-organizing maps. *Human movement science, 31*(2), 334-343.

Gudmundsson, J., & Horton, M. (2017). Spatio-temporal analysis of team sports. *ACM Computing Surveys (CSUR), 50*(2), 22.

Gudmundsson, J., & Wolle, T. (2014). Football analysis using spatio-temporal tools. *Comput. Environ. Urban Syst., 47*, 16-27.

Gyarmati, L., & Anguera, X. (2015). Automatic extraction of the passing strategies of soccer teams. *arXiv preprint arXiv:1508.02171*.

Gyarmati, L., Kwak, H., & Rodriguez, P. (2014). Searching for a unique style in soccer. *arXiv preprint arXiv:1409.0308*.

Halouani, J., Chtourou, H., Gabbett, T., Chaouachi, A., & Chamari, K. (2014). Small-sided games in team sports training: a brief review. *The Journal of Strength & Conditioning Research, 28*(12), 3594-3618.

Harper, L. D., West, D. J., Stevenson, E., & Russell, M. (2014). Technical performance reduces during the extra-time period of professional soccer match-play. *PloS one, 9*(10), e110995.

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.

Harvey, S., Cushion, C. J., Wegis, H. M., & Massa-Gonzalez, A. N. (2010). Teaching games for understanding in American high-school soccer: A quantitative data analysis using the game performance assessment instrument. *Physical Education and Sport Pedagogy, 15*(1), 29-54.

Harvey, S., & Gittins, C. (2014). Effects of integrating video-based feedback into a Teaching Games for Understanding soccer unit. *Agora para la educación física y el deporte, 16*(3), 271-290.

Haugen, T. A., Tønnessen, E., Hisdal, J., & Seiler, S. (2014). The role and development of sprinting speed in soccer. *International journal of sports physiology and performance, 9*(3), 432-441.

Herold, M., Goes, F., Nopp, S., Bauer, P., Thompson, C., & Meyer, T. (2019). Machine learning in men's professional football: Current applications and future directions for improving attacking play. *International Journal of Sports Science & Coaching*, 1747954119879350.

Herold, M., Kempe, M., Bauer, P., & Meyer, T. (2021). Attacking Key Performance Indicators in Soccer: Current Practice and Perceptions from the Elite to Youth Academy Level. *J Sports Sci Med, 20*(1), 158-169. doi:10.52082/jssm.2021.158

Herold, M., Kempe, M., Bauer, P., & Meyer, T. (2021). Attacking Key Performance Indicators in Soccer: Current Practice and Perceptions from the Elite to Youth Academy Level. *Journal of sports science & medicine, 20*(1), 158.

Hertzog, M. A. (2008). Considerations in determining sample size for pilot studies. *Research in nursing & health, 31*(2), 180-191.

Hewitt, A., Greenham, G., & Norton, K. (2016). Game style in soccer: what is it and can we quantify it? *International Journal of Performance Analysis in Sport, 16*(1), 355-372.

Hirano, S., & Tsumoto, S. (2005). *Grouping of soccer game records by multiscale comparison technique and rough clustering.* Paper presented at the Hybrid Intelligent Systems, International Conference, Rio de Janeiro.

Hobbs, J., Power, P., Sha, L., Ruiz, H., & Lucey, P. (2018). *Quantifying the value of transitions in soccer via spatiotemporal trajectory clustering.* Paper presented at the MIT Sloan Sports Analytics Conference, Boston.

Hook, C., & Hughes, M. (2001). Patterns of play leading to shots in Euro 2000. *Pass. com, 1*, 295-302.

Horn, R., Williams, M., & Ensum, J. (2002). Attacking in central areas: A preliminary analysis of attacking play in the 2001/2002 FA Premiership season. *Insight, 3*(5), 28-31.

Horton, M., Gudmundsson, J., Chawla, S., & Estephan, J. (2015). *Automated Classification of Passing in Football.* Paper presented at the Pacific-Asia Conference on Knowledge Discovery and Data Mining.

Hucaljuk, J., & Rakipović, A. (2011). *Predicting football scores using machine learning techniques.* Paper presented at the Proceedings of the 34th International Convention MIPRO.

Hughes, M. (2004). Performance analysis–a 2004 perspective. *International Journal of Performance Analysis in Sport, 4*(1), 103-109.

Hughes, M. (2015). Analysis of notation data: reliability. In *Essentials of Performance Analysis in Sport* (pp. 169-179): 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 soccer players by position. *Journal of Human Sport and Exercise, 7*(2), 402-412.

Hughes, M., & Churchill, S. (2005). *Attacking profiles of successful and unsuccessful teams in Copa America 2001.* Paper presented at the Science and football V: The proceedings of the fifth world congress on science and football.

Hughes, M., & Franks, I. (2005). Analysis of passing sequences, shots and goals in soccer. *J. Sports Sci., 23*(5), 509-514.

Hughes, M., & Franks, I. M. (2008). The essentials of performance analysis. *London: E. & FN Spon*.

Hughes, M., & Lovell, T. (2019). Transition to attack in elite soccer. *Journal of Human Sport & Exercise, 14*(1).

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

Ingersoll, K., Malesky, E., & Saiegh, S. M. (2017). Heterogeneity and team performance: Evaluating the effect of cultural diversity in the world's top soccer league. *Journal of Sports Analytics, 3*(2), 67-92.

James, N. (2006). Notational analysis in soccer: past, present and future. *International Journal of Performance Analysis in Sport, 6*(2), 67-81.

James, N., Jones, P., & Mellalieu, S. (2004). Possession as a performance indicator in soccer as a function of successful and unsuccessful teams. *Journal of Sports Sciences, 22*(6), 507-508.

James, N., Mellalieu, S., & Hollely, C. (2002). Analysis of strategies in soccer as a function of European and domestic competition. *Int. J. Perform. Anal. Sport, 2*(1), 85-103.

Janković, A., Leontijević, B., Jelušić, V., Pašić, M., & Mićović, B. (2011). Influence of tactics efficiency on results in serbian soccer super league in season 2009/2010. *Journal of Physical Education & Sport/Citius Altius Fortius, 11*(1).

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

Johnson, J. G. (2006). Cognitive modeling of decision making in sports. *Psychol. Sport Exerc., 7*(6), 631-652.

Jones, P., James, N., & Mellalieu, S. D. (2004). Possession as a performance indicator in soccer. *International Journal of Performance Analysis in Sport, 4*(1), 98-102.

Jordet, G., Bloomfield, J., & Heijmerikx, J. (2013). *The hidden foundation of field vision in English Premier League (EPL) soccer players.* Paper presented at the Proceedings of the MIT Sloan Sports Analytics Conference.

Joseph, A., Fenton, N. E., & Neil, M. (2006). Predicting football results using Bayesian nets and other machine learning techniques. *Knowledge Based Syst., 19*(7), 544-553.

Julious, S. A. (2005). Sample size of 12 per group rule of thumb for a pilot study. *Pharmaceutical Statistics: The Journal of Applied Statistics in the Pharmaceutical Industry, 4*(4), 287-291.

Kasap, S., & Kasap, N. (2005). Development of a database and decision support system for performance evaluation of soccer players.

Kelso, J. (1984). Phase transitions and critical behavior in human bimanual coordination. *Am. J. Physiol.-Regul. Integr. Comp. Physiol., 246*(6), R1000-R1004.

Kempe, M., & Goes, F. (2019). *Move it or lose it: Exploring the relation of defensive disruptiveness and team success* (2516-2314). Retrieved from

Kempe, M., Vogelbein, M., Memmert, D., & Nopp, S. (2014). Possession vs. direct play: evaluating tactical behavior in elite soccer. *International Journal of Sports Science, 4*(6A), 35-41.

Kempe, M., Vogelbein, M., & Nopp, S. (2016). The cream of the crop: Analysing FIFA world cup 2014 and Germany's title run. *J. Hum. Sport Exerc., 11*(1), 42-52. doi:10.14198/jhse.2016.111.04

Kempe, M., Vogelbein, M., & Nopp, S. (2016). The cream of the crop: Analysing FIFA World Cup 2014 and Germany’s title run.

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

Knauf, K., Memmert, D., & Brefeld, U. (2016). Spatio-temporal convolution kernels. *Mach. Learn., 102*(2), 247-273.

Król, M., Konefał, M., Chmura, P., Andrzejewski, M., Zając, T., & Chmura, J. (2017). Pass completion rate and match outcome at the World Cup in Brazil in 2014. *Polish Journal of Sport and Tourism, 24*(1), 30-34.

Krustrup, P., Mohr, M., Amstrup, T., Rysgaard, T., Johansen, J., Steensberg, A., . . . Bangsbo, J. (2003). The yo-yo intermittent recovery test: physiological response, reliability, and validity. *Medicine & Science in Sports & Exercise, 35*(4), 697-705.

Krustrup, P., Mohr, M., Steensberg, A., Bencke, J., Kjær, M., & Bangsbo, J. (2006). Muscle and blood metabolites during a soccer game: implications for sprint performance. *Medicine & Science in Sports & Exercise, 38*(6), 1165-1174.

Lago-Ballesteros, J., Lago-Penas, C., & Rey, E. (2012). The effect of playing tactics and situational variables on achieving score-box possessions in a professional soccer team. *J Sports Sci, 30*(14), 1455-1461. doi:10.1080/02640414.2012.712715

Lago-Ballesteros, J., Lago-Peñas, C., & Rey, E. (2012). The effect of playing tactics and situational variables on achieving score-box possessions in a professional soccer team. *J. Sports Sci., 30*, 1455-1461.

Lago-Peñas, C., Casais, L., Dellal, A., Rey, E., & Domínguez, E. (2011). Anthropometric and physiological characteristics of young soccer players according to their playing positions: relevance for competition success. *The Journal of Strength & Conditioning Research, 25*(12), 3358-3367.

Lago-Peñas, C., & Dellal, A. (2010). Ball possession strategies in elite soccer according to the evolution of the match-score: the influence of situational variables. *Journal of Human Kinetics, 25*, 93-100.

Lago-Peñas, C., Lago-Ballesteros, J., Dellal, A., & Gómez, M. (2010). Game-related statistics that discriminated winning, drawing and losing teams from the Spanish soccer league. *Journal of sports science & medicine, 9*(2), 288.

Lago-Peñas, C., Rey, E., Lago-Ballesteros, J., Casais, L., & Dominguez, E. (2009). Analysis of work-rate in soccer according to playing positions. *International Journal of Performance Analysis in Sport, 9*(2), 218-227.

Lago, C., & Martín, R. (2007). Determinants of possession of the ball in soccer. *Journal of sports sciences, 25*(9), 969-974.

Lanfranchi, P., & Taylor, M. (2001). *Moving with the ball: The migration of professional footballers*: Berg.

Larsen, C., Alfermann, D., & Christensen, M. (2012). Psychosocial Skills in a Youth Soccer Academy: A Holistic Ecological Perspective. *Sport Science Review, 21*.

Laube, P., Imfeld, S., & Weibel, R. (2005). Discovering relative motion patterns in groups of moving point objects. *Int.l J. Geog. Inf. Sci., 19*(6), 639-668.

Le, H. M., Carr, P., Yue, Y., & Lucey, P. (2017). *Data-driven ghosting using deep imitation learning.* Paper presented at the MIT Sloan Sports Analytics Conference, Boston.

Lepschy, H., Wäsche, H., & Woll, A. (2018). How to be successful in football: a systematic review. *The Open Sports Sciences Journal, 11*(1).

Link, D., Lang, S., & Seidenschwarz, P. (2016). Real time quantification of dangerousity in football using spatiotemporal tracking data. *PLoS One, 11*(12), e0168768.

Linke, D., Link, D., & Lames, M. (2018). Validation of electronic performance and tracking systems EPTS under field conditions. *PloS one, 13*(7), e0199519.

Linke, D., Link, D., & Lames, M. (2020). Football-specific validity of TRACAB's optical video tracking systems. *PLoS One, 15*(3), e0230179.

Liu, H., Gómez, M.-A., Gonçalves, B., & Sampaio, J. (2016). Technical performance and match-to-match variation in elite football teams. *Journal of sports sciences, 34*(6), 509-518.

Liu, H., Gomez, M.-Á., Lago-Peñas, C., & Sampaio, J. (2015). Match statistics related to winning in the group stage of 2014 Brazil FIFA World Cup. *Journal of sports sciences, 33*(12), 1205-1213.

Liu, H., Hopkins, W., Gómez, A. M., & Molinuevo, S. J. (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., Hopkins, W. G., & Gómez, M.-A. (2016). Modelling relationships between match events and match outcome in elite football. *European Journal of Sport Science, 16*(5), 516-525.

Llana, S., Burriel, B., Madrero, P., & Fernández, J. (2022). Is it worth the effort? Understanding and contextualizing physical metrics in soccer. *arXiv preprint arXiv:2204.02313*.

Lopes, A., Fonseca, S., Lese, R., & Baca, A. (2015). Using voronoi diagrams to describe tactical behaviour in invasive team sports: an application in basketball. *Cuadernos de Psicologia del Deporte, 15*(1), 123-130.

Lovell, T., Bocking, C., Fransen, J., & Coutts, A. (2018). A multidimensional approach to factors influencing playing level and position in a school-based soccer programme. *Science and Medicine in Football, 2*(3), 237-245.

Low, B., Rein, R., Raabe, D., Schwab, S., & Memmert, D. (2021). The porous high-press? An experimental approach investigating tactical behaviours from two pressing strategies in football. *Journal of sports sciences, 39*(19), 2199-2210.

Low, B., Rein, R., Schwab, S., & Memmert, D. (2022). Defending in 4-4-2 or 5-3-2 formation? small differences in footballers' collective tactical behaviours. *Journal of Sports Sciences, 40*(3), 351-363.

Loy, R. (1994). Wohin steuert der Fuβball. *Fussballtraining, 10*, 16-24.

Lucey, P., Bialkowski, A., Carr, P., Foote, E., & Matthews, I. A. (2012). *Characterizing multi-agent team behavior from partial team tracings: Evidence from the English premier league.* Paper presented at the 26th AAAI Conference on Artificial Intelligence.

Lucey, P., Bialkowski, A., Monfort, M., Carr, P., & Matthews, I. (2014). *quality vs quantity: Improved shot prediction in soccer using strategic features from spatiotemporal data.* Paper presented at the 8th Annual MIT Sloan Sports Analytics Conference.

Lucey, P., Oliver, D., Carr, P., Roth, J., & Matthews, I. (2013). *Assessing team strategy using spatiotemporal data.* Paper presented at the Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining.

Luhtanen, P., Belinskij, A., Häyrinen, M., & Vänttinen, T. (2001). A comparative tournament analysis between the EURO 1996 and 2000 in soccer. *International Journal of Performance Analysis in Sport, 1*(1), 74-82.

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

Maderer, D., Holtbrügge, D., & Schuster, T. (2014). Professional football squads as multicultural teams: Cultural diversity, intercultural experience, and team performance. *International Journal of Cross Cultural Management, 14*(2), 215-238.

Malmqvist, J., Hellberg, K., Möllås, G., Rose, R., & Shevlin, M. (2019). Conducting the pilot study: A neglected part of the research process? Methodological findings supporting the importance of piloting in qualitative research studies. *International Journal of Qualitative Methods, 18*, 1609406919878341.

McGarry, T., Anderson, D. I., Wallace, S. A., Hughes, M. D., & Franks, I. M. (2002). Sport competition as a dynamical self-organizing system. *Journal of Sports Sciences, 20*(10), 771-781.

McHale, I. G., & Relton, S. D. (2018). Identifying key players in soccer teams using network analysis and pass difficulty. *European Journal of Operational Research, 268*(1), 339-347.

McLean, S., Salmon, P. M., Gorman, A. D., Read, G. J., & Solomon, C. (2017). What's in a game? A systems approach to enhancing performance analysis in football. *PLoS One, 12*(2), e0172565.

Meerhoff, L. A., Goes, F. R., & Knobbe, A. (2019). *Exploring Successful Team Tactics in Soccer Tracking Data.* Paper presented at the Joint European Conference on Machine Learning and Knowledge Discovery in Databases.

Memmert, D., Lemmink, K. A., & Sampaio, J. (2017). Current approaches to tactical performance analyses in soccer using position data. *Sports Med., 47*(1), 1-10.

Memmert, D., & Perl, J. (2009). Game creativity analysis using neural networks. *J. Sports Sci., 27*(2), 139-149.

Memmert, D., Raabe, D., Schwab, S., & Rein, R. (2019). A tactical comparison of the 4-2-3-1 and 3-5-2 formation in soccer: A theory-oriented, experimental approach based on positional data in an 11 vs. 11 game set-up. *PloS one, 14*(1).

Milsom, J., Naughton, R., O'Boyle, A., Iqbal, Z., Morgans, R., Drust, B., & Morton, J. P. (2015). Body composition assessment of English Premier League soccer players: a comparative DXA analysis of first team, U21 and U18 squads. *Journal of sports sciences, 33*(17), 1799-1806.

Mitrotasios, M., & Armatas, V. (2014). Analysis of goal scoring patterns in the 2012 European Football Championship. *United States Sports Academy*.

Mohr, M., Krustrup, P., & Bangsbo, J. (2003). Match performance of high-standard soccer players with special reference to development of fatigue. *Journal of sports sciences, 21*(7), 519-528.

Montoliu, R., Martín-Félez, R., Torres-Sospedra, J., & Martínez-Usó, A. (2015). Team activity recognition in Association Football using a Bag-of-Words-based method. *Hum. Mov. Sci., 41*, 165-178.

Moreno, M. P., Moreno, A., Garcia-Gonzalez, L., Urena, A., Hernandez, C., & Del Villar, F. (2016). An Intervention Based on Video Feedback and Questioning to Improve Tactical Knowledge in Expert Female Volleyball Players. *Percept Mot Skills, 122*(3), 911-932. doi:10.1177/0031512516650628

Moura, F. A., Martins, L. E. B., Anido, R. O., Ruffino, P. R. C., Barros, R. M., & Cunha, S. A. (2013). A spectral analysis of team dynamics and tactics in Brazilian football. *Journal of sports sciences, 31*(14), 1568-1577.

Moura, F. A., Santana, J. E., Vieira, N. A., Santiago, P. R. P., & Cunha, S. A. (2015). Analysis of soccer players' positional variability during the 2012 UEFA European championship: A case study. *Journal of Human Kinetics, 47*(1), 225-236.

Muhamad, S., Norasrudin, S., & Rahmat, A. (2013). Differences in goal scoring and passing sequences between winning and losing team in UEFA-EURO Championship 2012. *International Journal of Humanities and Social Sciences, 7*(2), 332-337.

Nassis, G. P., Massey, A., Jacobsen, P., Brito, J., Randers, M. B., Castagna, C., . . . Krustrup, P. (2020). Elite football of 2030 will not be the same as that of 2020: Preparing players, coaches, and support staff for the evolution. In: Wiley Online Library.

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

Nelson, L. J., 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.

Njororai, W. W. S. (2013). Downward trend of goal scoring in world cup soccer tournaments (1930 to 2010). *Journal of Coaching Education, 6*(1), 111-120.

O'donoghue, P. (2009). *Research methods for sports performance analysis*: Routledge.

O'Donoghue, P. (2004). Sources of variability in time-motion data; measurement error and within player variability in work-rate. *International Journal of Performance Analysis in Sport, 4*(2), 42-49.

O'Donoghue, P., Papadimitriou, K., Gourgoulis, V., & Haralambis, K. (2012). Statistical methods in performance analysis: an example from international soccer. *International Journal of Performance Analysis in Sport, 12*(1), 144-155.

O'Donoghue, P., Rudkin, S., Bloomfield, J., Powell, S., Cairns, G., Dunkerley, A., . . . Bowater, J. (2005). Repeated work activity in English FA Premier League soccer. *International Journal of Performance Analysis in Sport, 5*(2), 46-57.

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).

Olsen, E., & Larsen, O. (1997). Use of match analysis by coaches. *Science and football III, 3*, 209-220.

Olthof, S. B., Frencken, W. G., & Lemmink, K. A. (2019). When something is at stake: Differences in soccer performance in 11 vs. 11 during official matches and training games. *Journal of strength and conditioning research, 33*(1), 167.

Orth, D., Davids, K., Araújo, D., Renshaw, I., & Passos, P. (2014). Effects of a defender on run-up velocity and ball speed when crossing a football. *European Journal of Sport Science, 14*(sup1), S316-S323.

Owen, A., Twist, C., & Ford, P. (2004). Small-sided games: the physiological and technical effect of altering pitch size and player numbers. *Insight, 7*(2), 50-53.

Pappalardo, L., & Cintia, P. (2017). Quantifying the relation between performance and success in soccer. *Adv. Complex Syst., 21*(3), 1750014.

Pappalardo, L., Cintia, P., Rossi, A., Massucco, E., Ferragina, P., Pedreschi, D., & Giannotti, F. (2019). A public data set of spatio-temporal match events in soccer competitions. *Scientific data, 6*(1), 1-15.

Partington, M., Cushion, C. J., Cope, E., & Harvey, S. (2015). The impact of video feedback on professional youth football coaches' reflection and practice behaviour: A longitudinal investigation of behaviour change. *Reflective practice, 16*(5), 700-716.

Passos, P., Amaro E Silva, R., Gomez-Jordana, L., & Davids, K. (2020). Developing a two-dimensional landscape model of opportunities for penetrative passing in association football–Stage I. *Journal of Sports Sciences, 38*(21), 2407-2414.

Paul, D. J., Bradley, P. S., & Nassis, G. P. (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.

Pena, J. L., & Touchette, H. (2012). A network theory analysis of football strategies. *arXiv preprint arXiv:1206.6904*.

Perin, C., Vuillemot, R., Stolper, C., Stasko, J., Wood, J., & Carpendale, S. (2018). *State of the art of sports data visualization.* Paper presented at the Computer Graphics Forum.

Perl, J., Grunz, A., & Memmert, D. (2013). Tactics analysis in soccer–an advanced approach. *Int. J. Comput. Sci. Sport, 12*(1), 33-44.

Perl, J., & Memmert, D. (2017). A Pilot study on offensive success in soccer based on space and ball control–key performance indicators and key to understand game dynamics. *International Journal of Computer Science in Sport, 16*(1), 65-75.

Pina, T. J. L. F. M. d. (2017). *Successful team synergies: a social network analysis on high performing soccer teams in the UEFA Champions League.*

Pinto, B. B. D. C. (2021). *How can the usage of data analytics help football clubs create a competitive advantage: a research on Liverpool football club.*

Pizarro, A. P., Domínguez, A. M., Serrano, J. S., García-González, L., & del Villar Álvarez, F. (2017). The effects of a comprehensive teaching program on dribbling and passing decision-making and execution skills of young footballers. *Kinesiology, 49*(1).

Pollard, R., Ensum, J., & Taylor, S. (2004). Estimating the probability of a shot resulting in a goal: The effects of distance, angle and space. *International Journal of Soccer and Science, 2*(1), 50-55.

Pons, E., García-Calvo, T., Resta, R., Blanco, H., López del Campo, R., Díaz García, J., & Pulido, J. J. (2019). A comparison of a GPS device and a multi-camera video

technology during official soccer matches: Agreement between systems. *PLoS One, 14*(8), e0220729.
Power, P., Ruiz, H., Wei, X., & Lucey, P. (2017). *Not all passes are created equal: Objectively measuring the risk and reward of passes in soccer from tracking data.* Paper presented at the Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.
Pratas, J. M., Volossovitch, A., & Carita, A. I. (2018). Goal scoring in elite male football: A systematic review.
Práxedes, A., Del Villar Álvarez, F., Moreno, A., Gil-Arias, A., & Davids, K. (2019). Effects of a nonlinear pedagogy intervention programme on the emergent tactical behaviours of youth footballers. *Physical Education and Sport Pedagogy, 24*(4), 332-343.
Prieto, J., Gómez, M.-Á., & Sampaio, J. (2015). From a static to a dynamic perspective in handball match analysis: a systematic review. *Open Sports Sci. J., 8*(1).
Priyadarshana, W., & Sofronov, G. (2014). Multiple break-points detection in array CGH data via the cross-entropy method. *IEEE/ACM Transactions on Computational Biology and Bioinformatics, 12*(2), 487-498.
Quintana, M., Aguilera-Castells, J., Solana-Tramunt, M., Morales, J., & Nieto, A. (2019). Effects of Video Feedback on Kicking Performance and Temporal Patterns in U-10 Soccer Players: 810 Board# 44 May 29 2: 00 PM-3: 30 PM. *Medicine & Science in Sports & Exercise, 51*(6S), 199.
Rampinini, E., Impellizzeri, F. M., Castagna, C., Coutts, A. J., & 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.
Rathke, A. (2017). An examination of expected goals and shot efficiency in soccer. *J. Hum. Sport Exerc., 12*(2). doi:10.14198/jhse.2017.12.Proc2.05
Ravé, G., Granacher, U., Boullosa, D., Hackney, A. C., & Zouhal, H. (2020). How to Use Global Positioning Systems (GPS) Data to Monitor Training Load in the "Real World" of Elite Soccer. *Frontiers in Physiology*, 944.
Read, P. J., Jimenez, P., Oliver, J. L., & Lloyd, R. S. (2018). Injury prevention in male youth soccer: Current practices and perceptions of practitioners working at elite English academies. *Journal of sports sciences, 36*(12), 1423-1431. doi:10.1080/02640414.2017.1389515
Redwood-Brown, A. (2008). Passing patterns before and after goal scoring in FA Premier League Soccer. *International Journal of Performance Analysis in Sport, 8*(3), 172-182.
Reep, C., & Benjamin, B. (1968). Skill and chance in association football. *Journal of the Royal Statistical Society. Series A (General), 131*(4), 581-585.
Rees, G., James, N., Hughes, M., Taylor, J., & Vučković, G. (2010a). The effect of match status on attacking strategies in the English Championship. *Research Methods and Performance Analysis*, 172.
Rees, G., James, N., Hughes, M., Taylor, J., & Vučković, G. (2010b). The use of zone 14 as a strategic attacking area in the English Championship. *Research Methods and Performance Analysis*, 205.
Reeves, M. J., & Roberts, S. J. (2013). Perceptions of performance analysis in elite youth football. *International Journal of Performance Analysis in Sport, 13*(1), 200-211.
Rein, R., & Memmert, D. (2016a). Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *SpringerPlus, 5*(1), 1410.
Rein, R., & Memmert, D. (2016b). Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science. *SpringerPlus, 5*(1), 1-13.

Rein, R., Raabe, D., & Memmert, D. (2017). “Which pass is better?” Novel approaches to assess passing effectiveness in elite soccer. *Human movement science, 55*, 172-181.

Rein, R., Raabe, D., Perl, J., & Memmert, D. (2016). *Evaluation of changes in space control due to passing behavior in elite soccer using Voronoi-cells.* Paper presented at the Proceedings of the 10th international symposium on computer science in sports (ISCSS).

Ric, A., Torrents, C., Gonçalves, B., Torres-Ronda, L., Sampaio, J., & Hristovski, R. (2017). Dynamics of tactical behaviour in association football when manipulating players' space of interaction. *PLoS One, 12*(7), e0180773.

Rice-Coates, C. (2017). THOMAS MÜLLER: THE FIRST AND POSSIBLY LAST RAUMDEUTER.

Rossi, A., Pappalardo, L., Cintia, P., Iaia, F. M., Fernàndez, J., & Medina, D. (2018). Effective injury forecasting in soccer with GPS training data and machine learning. *PloS one, 13*(7), e0201264.

Ruiz-Ruiz, C., Fradua, L., Fernandez-Garcia, A., & Zubillaga, A. (2013). Analysis of entries into the penalty area as a performance indicator in soccer. *Eur J Sport Sci, 13*(3), 241-248. doi:10.1080/17461391.2011.606834

Ruiz, H., Lisboa, P., Neilson, P., & Gregson, W. (2015). *Measuring scoring efficiency through goal expectancy estimation.* Paper presented at the ESANN 2015 Proceedings of the European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning.

Rumpf, M. C., Silva, J. R., Hertzog, M., Farooq, A., & Nassis, G. (2017). Technical and physical analysis of the 2014 FIFA World Cup Brazil: winners vs. losers. *J Sports Med Phys Fitness, 57*(10), 1338-1343.

Russell, M., Benton, D., & Kingsley, M. (2011). The effects of fatigue on soccer skills performed during a soccer match simulation. *International journal of sports physiology and performance, 6*(2), 221-233.

Sampaio, J., & Maçãs, V. (2012). Measuring tactical behaviour in football. *International journal of sports medicine, 33*(05), 395-401.

Santos, P., Lago-Peñas, C., & García-García, O. (2017). The influence of situational variables on defensive positioning in professional soccer. *International Journal of Performance Analysis in Sport, 17*(3), 212-219.

Santos, S., Coutinho, D., Gonçalves, B., Schöllhorn, W., Sampaio, J., & Leite, N. (2018). Differential learning as a key training approach to improve creative and tactical behavior in soccer. *Research quarterly for exercise and sport, 89*(1), 11-24.

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

Sarmento, H., Clemente, F. M., Harper, L. D., Costa, I. T. d., Owen, A., & Figueiredo, A. J. (2018). Small sided games in soccer–a systematic review. *International Journal of Performance Analysis in Sport, 18*(5), 693-749.

Sarmento, H., Marcelino, R., Anguera, M. T., CampaniÇo, J., Matos, N., & LeitÃo, J. C. (2014). Match analysis in football: a systematic review. *J. Sports Sci., 32*(20), 1831-1843.

Sathyamorthy, D., Shafii, S., Amin, Z. F. M., Jusoh, A., & Ali, S. Z. (2016). Evaluation of the trade-off between Global Positioning System (GPS) accuracy and power saving from reduction of number of GPS receiver channels. *Applied Geomatics, 8*(2), 67-75.

Schreurs, M. J., Benjaminse, A., & Lemmink, K. A. (2017). Sharper angle, higher risk? The effect of cutting angle on knee mechanics in invasion sport athletes. *Journal of biomechanics, 63*, 144-150.

Schulze, E., Mendes, B., Maurício, N., Furtado, B., Cesário, N., Carriço, S., & Meyer, T. (2018). Effects of positional variables on shooting outcome in elite football. *Sci. Med. Football, 2*(2), 93-100.

Setterwall, D. (2003). Computerised video analysis of football-technical and commercial possibilities for football coaching. *Unpublished Masters Thesis. Stockholms Universitet*.

Shafizadeh, M., Lago-Penas, C., Gridley, A., & Platt, G. K. (2014). Temporal analysis of losing possession of the ball leading to conceding a goal: a study of the incidence of perturbation in soccer. *International Journal of Sports Science & Coaching, 9*(4), 627-636.

Silva, B., Garganta, J., Santos, R., & Teoldo, I. (2014). Comparing tactical behaviour of soccer players in 3 vs. 3 and 6 vs. 6 small-sided games. *Journal of human kinetics, 41*, 191.

Simiyu, W. W. N. (2014). Timing of goals scored in selected european and South American Football Leagues, FIFA and UEFA tournaments and the critical phases of a match.

Skinner, G. K., & Freeman, G. (2009). Soccer matches as experiments: how often does the 'best'team win? *Journal of Applied Statistics, 36*(10), 1087-1095.

Smith, M. R., Coutts, A. J., Merlini, M., Deprez, D., Lenoir, M., & Marcora, S. M. (2016). Mental fatigue impairs soccer-specific physical and technical performance. *Med Sci Sports Exerc, 48*(2), 267-276.

Spearman, W. (2018). *Beyond expected goals.* Paper presented at the MIT Sloan Sports Analytics Conference, Boston.

Stanhope, J. (2001). An investigation into possession with respect to time, in the soccer world cup 1994. *Notational analysis of sport III*, 155-162.

Stein, M., Janetzko, H., Lamprecht, A., Breitkreutz, T., Zimmermann, P., Goldlücke, B., . . . Keim, D. A. (2017). Bring it to the pitch: Combining video and movement data to enhance team sport analysis. *IEEE transactions on visualization and computer graphics, 24*(1), 13-22.

Steiner, S. (2018). Passing decisions in football: Introducing an empirical approach to estimating the effects of perceptual information and associative knowledge. *Frontiers in psychology, 9*, 361.

Steiner, S. (2018). Passing Decisions in Football: Introducing an Empirical Approach to Estimating the Effects of Perceptual Information and Associative Knowledge. *Front Psychol, 9*, 361. doi:10.3389/fpsyg.2018.00361

Steiner, S., Rauh, S., Rumo, M., Sonderegger, K., & Seiler, R. (2019). Outplaying opponents—a differential perspective on passes using position data. *German Journal of Exercise and Sport Research, 49*(2), 140-149.

Sternberg, R. J., & Lubart, T. I. (1999). The concept of creativity: Prospects and paradigms. *Handbook of creativity, 1*(3-15).

Stoszkowski, J., & Collins, D. (2016). Sources, topics and use of knowledge by coaches. *Journal of sports sciences, 34*(9), 794-802.

Szczepański, Ł., & Mchale, I. (2016). Beyond completion rate: evaluating the passing ability of footballers. *J. R. Stat. Soc., 178*(4), 513–533.

Szwarc, A. (2004a). Effectiveness of Brazilian and German teams and the teams defeated by them during the 17th Fifa World Cup. *Kinesiology: International journal of fundamental and applied kinesiology, 36*(1), 83-89.

Szwarc, A. (2004b). EFFECTIVENESS OF BRAZILIAN AND GERMAN TEAMS AND THE TEAMS DEFEATED BY THEM DURING THE 17TH FIFA WORLD CUP. *Kinesiology, 36*(1).

Taki, T., & Hasegawa, J.-i. (2000). *Visualization of dominant region in team games and its application to teamwork analysis.* Paper presented at the Proceedings Computer Graphics International 2000.

Tax, N., & Joustra, Y. (2015). Predicting the Dutch football competition using public data: A machine learning approach. *IEEE Trans. Knowl. Data Eng., 10*(10), 1-13.

Taylor, J. B., Mellalieu, S. D., James, N., & Shearer, D. A. (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. B., Wright, A. A., Dischiavi, S. L., Townsend, M. A., & Marmon, A. R. (2017). Activity demands during multi-directional team sports: a systematic review. *Sports medicine, 47*(12), 2533-2551.

Taylor, S., Ensum, J., & Williams, M. (2002). A quantitative analysis of goals scored. *Insight, 5*(4), 28-31.

Tenga, A., Holme, I., Ronglan, L. T., & Bahr, R. (2010a). Effect of playing tactics on achieving score-box possessions in a random series of team possessions from Norwegian professional soccer matches. *J Sports Sci, 28*(3), 245-255. doi:10.1080/02640410903502766

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

Tenga, A., Mortensholm, A., & O'Donoghue, P. (2017). Opposition interaction in creating penetration during match play in elite soccer: evidence from UEFA champions league matches. *Int. J. Perform. Anal. Sport, 17*(5), 802-812.

Tenga, A., & Sigmundstad, E. (2011). Characteristics of goal-scoring possessions in open play: Comparing the top, in-between and bottom teams from professional soccer league. *International Journal of Performance Analysis in Sport, 11*(3), 545-552.

Thakkar, P., & Shah, M. (2021). An assessment of football through the lens of data science. *Annals of Data Science, 8*(4), 823-836.

Thompson, S. W. (2020). The challenges of collaborative working: bridging the gap between research and practice. *International Journal of Strength and Conditioning, 1*(1).

Topál, D., Matyasovszkyt, I., Kern, Z., & Hatvani, I. G. (2016). Detecting breakpoints in artificially modified-and real-life time series using three state-of-the-art methods. *Open geosciences, 8*(1), 78-98.

Vagias, W. M. (2006). Likert-type scale response anchors. *Clemson International Institute for Tourism & Research Development, Department of Parks, Recreation and Tourism Management. Clemson University*.

Vecer, J. (2014). Crossing in soccer has a strong negative impact on scoring: Evidence from the English premier league the German Bundesliga and the World Cup 2014. *Available at SSRN 2225728*.

Vilar, L., Araújo, D., Davids, K., & Bar-Yam, Y. (2013). Science of winning soccer: Emergent pattern-forming dynamics in association football. *Journal of systems science and complexity, 26*(1), 73-84.

Vilar, L., Araújo, D., Davids, K., & Button, C. (2012). The role of ecological dynamics in analysing performance in team sports. *Sports Med., 42*(1), 1-10.

Wagenaar, M., Okafor, E., Frencken, W., & Wiering, M. A. (2017). *Using Deep Convolutional Neural Networks to Predict Goal-scoring Opportunities in Soccer.* Paper presented at the ICPRAM.

Wallace, J. L., & Norton, K. I. (2014). Evolution of World Cup soccer final games 1966-2010: game structure, speed and play patterns. *J. Sci. Med. Sport, 17*, 223-228.

Wei, X., Sha, L., Lucey, P., Morgan, S., & Sridharan, S. (2013). *Large-scale analysis of formations in soccer.* Paper presented at the 2013 international conference on digital image computing: techniques and applications (DICTA).

Weldon, A., Duncan, M. J., Turner, A., Sampaio, J., Noon, M., Wong, D., & Lai, V. W. (2021). Contemporary practices of strength and conditioning coaches in professional soccer. *Biology of Sport, 38*(3), 377-390.

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.

Winkler, W. (1996). Computer/video analysis in German soccer. In M. Hughes (Ed.), *Notational Analysis of Sport* (pp. 19-31). Cardiff: UWIC.

Wisloeff, U., Helgerud, J., & Hoff, J. (1998). Strength and endurance of elite soccer players. *Medicine and science in sports and exercise, 30*(3), 462-467.

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., Atkins, S., Polman, R., Jones, B., & Sargeson, L. (2011). Factors associated with goals and goal scoring opportunities in professional soccer. *International Journal of Performance Analysis in Sport, 11*(3), 438-449.

Xinyu, W., Long, S., Lucey, P., Morgan, S., & Sridharan, S. (2013). *Large-scale analysis of formations in Soccer.* Paper presented at the 2013 International Conference on the Digital Image Computing: Techniques and Applications (DICTA).

Yamada, H., & Hayashi, Y. (2015). Characteristics of goal scoring crosses in International Soccer tournaments. *Football Science, 12*, 24-32.

Yang, G., Leicht, A. S., Lago, C., & Gómez, M.-Á. (2018). Key team physical and technical performance indicators indicative of team quality in the soccer Chinese super league. *Research in Sports Medicine, 26*(2), 158-167.

Yi, Q., Jia, H., Liu, H., & Gómez, M. Á. (2018). Technical demands of different playing positions in the UEFA Champions League. *International Journal of Performance Analysis in Sport, 18*(6), 926-937.

Yiannakos, A., & Armatas, V. (2006). Evaluation of the goal scoring patterns in European Championship in Portugal 2004. *International Journal of Performance Analysis in Sport, 6*(1), 178-188.

Young, W. B., & Murray, M. P. (2017). Reliability of a field test of defending and attacking agility in Australian football and relationships to reactive strength. *The Journal of Strength & Conditioning Research, 31*(2), 509-516.

Yue, Z., Broich, H., & Mester, J. (2014). Statistical analysis for the soccer matches of the first Bundesliga. *International Journal of Sports Science & Coaching, 9*(3), 553-560.

Yue, Z., Broich, H., Seifriz, F., & Mester, J. (2008). Mathematical analysis of a soccer game. Part I: individual and collective behaviors. *Stud. Appl. Math., 121*(3), 223-243.

Appendix A. Algorithm for Finding Local Maximums in Time-Series Data

Data: Pressures
gradients ← Diff(pressures);
gradient_signs ← Sign(gradients);

Examples:
pressures ← [0, 0, 2, 5, 6, 4, 3, 1, 0, 3];
gradients ← [0, 2, 3, 1, −2, −1, −2, −1, 3];
gradient_signs ← [0, 1, 1, 1, −1, −1, −1, −1, 1];
Starting with time-series data pressures, a 1-dimensional array of n pressure values. Diff takes a 1-dimensional array, shifts the values, and subtracts from itself. The results are an array of length $n - 1$ giving the difference in value between consecutive values in the original array. Sign simply gives the sign of each element of the array; 0, 1 (positive), or -1 (negative). The result of Sign is an array of 0, 1, and -1, depending on the sign of the value in the original array. From the array gradient_signs, instances of $[\ldots, \alpha, -1, \ldots]$ were found, with $\alpha \in$ (Acar et al., 2008), which corresponds to a local maximum and the start of a decrease in pressure. A consecutive run of -1 values correspond to a sustained decrease in pressure

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